DIFFERENT EDUCATIONAL STRUCTURES AND THEIR ECONOMIC IMPACT ON INDIVIDUALS AND THE ECONOMY

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Chapter 1

Introduction

Following the seminal work by Schultz (1961), Becker (1962), and Mincer (1974), many researchers have investigated the effect of education—of an investment in human capital—on monetary outcomes for individuals. Empirical evidence identifying the returns to education is vast, thereby corroborating the positive association between the amount of acquired human capital and wages (Wössmann & Schütz, 2006). In addition to these monetary effects at the individual level, education has an impact on the entire economy. Wössmann (2008) argues that the most seminal finding in economic research of the last two decades is the relation between growth and innovation. Moreover, he argues that a fundamental determinant of innovation (and, thus, of growth) is the quality of education. Education is thus a fundamental determinant of outcomes at not only the individual level but also that of the economy.

However, despite the economic importance of education on outcomes of both individuals and the economy, empirical evidence on the effect of different educational structures on these outcomes is limited. Education—i.e., the structuring of educational careers or systems—differs in terms of three different factors: *level*, *type*, and *field*. *Level* is the acquired number of years of schooling (e.g., Card 1999, 2001), i.e., whether an individual completes more or fewer years of education and acquires an educational degree at the primary, secondary tertiary level (e.g., Aghion, Boustan, Hoxby & Vandenbussche, 2005). *Type* is the distinction between academic, vocational, and mixed educational careers (i.e., those that combine academic and vocational education) (e.g., Tuor & Backes-Gellner, 2010). *Field* involves the specific subject area, such as business, engineering or health, in which individuals are educated (e.g., Altonji, Blom, & Meghir, 2012). Education is thus a heterogeneous good involving different types, levels and fields. Combining these factors in a particular way results in different educational structures. The academic type and the tertiary level, for example, characterize a widespread educational structure: academic universities. The impact of these universities on the economy and on individuals might differ from the impact of educational structures combining other factors. Taking into account these different dimensions of educational structures—the way in which educational careers or systems are structured—is therefore fundamental to understand how education affects the economy and individuals.

Most research thus far, particularly in the Anglo-Saxon countries, has focused on the factor level by investigating the effect of more or fewer years on the (monetary) outcomes of the economy and of individuals. The other factors, namely, type and field have mostly been neglected. In this dissertation, I narrow this gap by focusing on these factors and by investigating their effect on (a) the economy and (b) individuals. The analyses at both levels thereby focus on dimensions of educational structures and outcomes thus far neglected in the literature.

In the analysis at the level of the economy, I investigate the effect of tertiary vocational education. Many researchers have investigated the impact of universities on the economy; empirical evidence on the effect of tertiary academic education is therefore vast. Research investigating the effect of tertiary vocational education, however, is still needed. To analyze the impact of this particular educational structure on the economy, I focus on the outcome innovation. For the economy, innovation is essential because it is related to growth and because it can generate sustainable competitive advantages (Harhoff, 2008; Wössmann, 2008). In the analysis at the level of the individuals, I focus on the factors constituting the differences among educational structures. In other words, I focus on the type and the field of education, whose different combinations lead to particular educational structures, and analyze the factors' importance for individual-level outcomes. I thereby analyze two central aspects of individual decision-making that the literature has thus far not considered. First, most studies consider the decision either between different types (vocational vs. academic) or among particular fields (e.g., health vs. business). Second, most research investigating the effect of education on individual-level outcomes focuses on the average returns of educational careers and neglects the risk associated with these decisions. In my analyses at the individual level, I take into account both factors, type and field of education, and study how risky they are. My analysis thus shows how the earnings risk inherent in different educational structures relates to the two factors type and field.

Chapter two to four of this dissertation contain the analyses at the level of the economy and investigate the effect of tertiary vocational education on innovation. Previous research shows the importance of education on the firms' innovation activities (e.g., Aghion et al., 2005; Bellucci & Pennacchio, 2015; Blundell, Dearden, Meghir & Sianesi, 1999; Toivanen & Väänanen; Valero & Van Reenen, 2016; Vandenbussche, Aghion & Meghir, 2006). However, most of these studies do not take into account differences in educational structures; instead, they focus exclusively on the effect of the academic type of education, i.e., the effect of conventional academic universities, on the economy's innovation activity. They, therefore, investigate the effect of basic research, the type of research that academic universities predominantly conduct, on innovation (e.g., Rosenberg & Nelson, 1994). Moreover, most studies that differentiate between the academic and the vocational type of education suggest that academic education implies a faster adoption of new technologies than vocational education does (Krueger & Kumar, 2004a, 2004b).

However, Rupietta and Backes-Gellner (2015) show a positive relationship between upper-secondary vocational education and the economy's innovative performance, analyzing the impact of the Swiss vocational education and training (VET) system on firms' innovative activities. They, therefore, show that both academic and vocational education have a positive effect on innovation. Nevertheless, whether vocational education at the tertiary level also increases the economy's innovativeness remains unclear. Drucker and Goldstein emphasize the "need for research that carefully examines the effects of variations in higher education policy on university-induced outcomes," as such research constitutes the basis to explain how universities (and thus education) affect the economy (2007: 40).

In the second chapter of this dissertation, I investigate the effect on the economy's innovative activities of an educational structure that the literature has thus far not considered: tertiary vocational education. To answer this question, I focus on Universities of Applied Sciences (UAS) in the educational fields of engineering, IT, chemistry, and the life sciences. Although located at the same level as conventional academic universities, UAS differ from academic universities because they are vocational institutions whose teaching and research focus on *applying* knowledge and scientific methods. To analyze the impact of these UAS on the economy's innovation activities, I exploit the regional and temporal variation of their establishment in Switzerland in the mid-1990s and apply difference-in-differences estimations: First, I reconstruct the history of each of the UAS to show where they are located and when they opened their doors. Second, I discuss the potential mechanisms of the innovation effect—direct spillovers such as UAS graduates entering the labor market, and the collaboration between UAS and firms, and indirect spillovers such as a potential increase in regional entrepreneurial activities—and define the (geographical) area of influence of a UAS, namely, the "treated regions."

I measure regional innovation by patenting activity and use patent data from the European Patent Office (EPO). The locations of the patent applicants allow me to construct the dependent variable for innovation quantity, the number of patent applications in each year and in each municipality.

Comparing the innovation quantity of the treated regions with that of untreated regions (i.e., areas that did not—or not yet—receive a UAS campus) before the establishment of UAS, I show that the trends of these treated and untreated regions do not differ. As the two regions exhibited the same innovation patterns before the UAS reform, I can use the difference-in-differences (DID) method to estimate the unbiased effect of UAS on innovation. The results of this DID estimation show an average increase in innovation quantity of 13 percent as a consequence of the establishment of UAS.

In a number of robustness checks, I investigate whether this effect is robust to a number of critical changes in estimations: First, I show that the potential contamination of treated and untreated regions as a result of individuals moving from a treated to a non-treated region do not distort the results. Second, when I control for unobservable time-constant municipality characteristics, I still find a strong innovation effect. Third, I investigate how the increase in innovation quantity develops over different post-treatment years and show that this development is in line with my theoretical expectations. Fourth, I test for an alternative source that might have also caused the innovation effect—the expansion of academic universities—and show that an increase in academic graduates does not affect the increase in innovation that we observe. Moreover, my results indicate that a large part of the innovation effect relates to one form of direct spillovers, i.e., UAS graduates entering the labor market and enhancing its quality.

In the third chapter of this dissertation, I focus on qualitative innovation factors of the innovation increase that I measure. The literature on innovation economics shows large differences in the economic value of patents and, consequently, the necessity of further quality indicators (e.g., Griliches, 1979; 2007; Harhoff, Scherer, & Vopel, 2003). For the concept of patent quality, I discuss the different methods and indicators for measuring patent quality. To estimate the effect of the establishment of UAS on the quality of innovation, I use the following indicators: grant status, forward citations, claims, and patent family size. The database for these estimations is again the EPO. For all four indicators, treated and untreated regions show parallel trends before the UAS reform, allowing me to apply the DID method. The DID estimations reveal an increase of 1.3 to 3.1 percent for the forward citations indicators, and an increase of 6.8 to 10.6 percent for the grant status, claims, and patent family size indicators. Thus the establishment of UAS increases both innovation quantity and quality.

In the fourth chapter of this dissertation, I focus on the beneficiaries of the innovation increase. First, I focus on different types of patent applicants and investigate whether they equally profit from the spillovers of UAS. To investigate the impact of UAS on heavy and light applicants—who can be associated with large firms and small and medium-sized firms—I use a subsample excluding the heavy applicants. To estimate the effect on first-time applicants (which are associated with newly founded firms and firms that did not patent before the establishment of UAS campuses), I restrict the patent database to applicants who appear during our observation period for the first time. The results show that all types of applicants profit from UAS: Innovation activities increase for both heavy and light applicants, although the heavy ones exhibit a larger effect. Finally, the number for first-time applicants increases by 3.5 percent.

Second, focusing on rural areas, I analyze regional heterogeneity in innovation activities. The literature shows that innovation activities build regional clusters and that rural areas profit less from these clusters (e.g., Acs, Anselin & Varga, 2003). As the UAS reform was particularly aimed at increasing the innovative performance of such rural areas, I investigate whether rural municipalities within UAS campus regions increase their innovative activities more than rural municipalities without UAS do. The results show an increase of 4.8 percent for UAS campus regions, a substantial and economically important effect. UAS thus constitute a means to foster innovation activities outside metropolitan areas.

My analyses at the level of the economy in chapters two, three, and four thus emphasize the importance of different dimensions of educational structures when analyzing the effect of education on economic outcomes. Focusing on a particular educational structure thus far neglected in the literature, I demonstrate that tertiary vocational education has a substantial impact on the economy. I thereby show that the underlying characteristics of this particular educational structure, i.e., the application of knowledge and scientific methods in UAS teaching and research, are essential drivers of regional innovation activities.

However, whether different educational structures affect outcomes not only at the level of the economy but also at that of the individuals remains unclear. In the fifth chapter, I focus on the factors that characterize different educational structures, namely the type and the field of education. I analyze the differences among educational structures—focusing on the different combinations of the factors type and field of education—to investigate how important the two factors are for economic outcomes at the individual level. Most literature has investigated either the effect of the type or the effect of the field of education on monetary outcomes at the individual level. For the type of education, the literature shows mixed results of academic and vocational education on the individual's returns to education: Some studies find higher returns for academic education (e.g., Conlon, 2005), while others find reasonable or even higher returns for vocational education (e.g., Wolter & Weber, 1999). For the field of education, studies find consistent results and the highest returns for engineering, health, and business, and the lowest returns for education, the social sciences, and the humanities (e.g., Thomas & Zhang, 2005). However, most studies analyzing the effect of the type and field of education on earnings take into account only one of the two factors. Moreover, most studies analyzing the importance of different educational structures focus only on profitability, thereby neglecting a second fundamental aspect of the individuals' educational decisions—the risk associated with educational factors. In chapter five, I consider both factors, type and field of education, and investigate their relative importance in terms of risk.

To analyze the relative importance of these two factors in determining risk, I decompose the variance of earnings according to the two educational factors, type and field of education. First, I estimate Mincer-type earnings equations using dummies for the type of education and for subject areas. For the type of education, I distinguish among purely vocational, purely academic, and mixed education careers (a combination of vocational and academic educations). For the subject areas, I follow the literature on education economics and create five broad fields of education, i.e., subject areas (e.g., Altonji et al., 2012; Finnie & Frenette, 2003; Rumberger & Thomas, 1993): commercial, health, STEM, social & service, and combined subject areas. Second, I calculate the variance of these returns to types of education and of these returns to the subject areas and decompose the variance in earnings according to these two factors. This variance decomposition thus allows me to quantify the separate contribution of the type of education and subject area to the variance in earnings.

For the analysis, I use the Swiss Adult Education Survey from 2011 and focus on individuals who all have a tertiary education degree. The results of the Mincer-type earnings equations show that both factors, type of education and subject area, have a statistically significant effect on the individual's returns to education. Whereas academic and mixed educations show the highest returns for the factor type education, commercial is most profitable for the factor subject area. The results of the variance decomposition show that the percent of the variance in earnings explained by the subject area is nearly double that explained by the type of education: 17 percent of the explained variance in earnings is attributable to the subject area, whereas only 9 percent is attributable to the type of education. The individuals' earnings thus vary more with the subject area than with the type of education, implying that decisions made within the subject area are riskier than those made by the type of education.

In the sixth chapter, I summarize the main findings and draw conclusions for policy makers and future research. Throughout the three chapters, empirical evidence demonstrates that education is not a homogeneous good. Heterogeneity in education, i.e., differences in educational structures and their underlying factors, constitute an important determinant of outcomes of the economy and of individuals. At the level of the economy, most research has investigated the effect of academic universities on innovation, thus focusing on tertiary academic education and neglecting the vocational type. My analyses demonstrate that tertiary vocational education—an educational structure thus far neglected in the literature—has a substantial impact on the economy. My results show an increase in both the quantity and the quality of innovation and that all types of applicants and areas—including the rural ones—profit from this particular educational structure. To foster the innovative performance of the economy, tertiary vocational education thus constitutes an effective alternative to academic universities.

At the level of the individuals, the literature has thus far focused either on the type or on the field of education. Analyses on the relative importance of these two factors were therefore not possible. Moreover, most of these studies have investigated the effect of education on profitability, thereby neglecting a second fundamental aspect of educational investments: the risk. In my analysis, I consider both factors at the same time and show their relative importance in determining the individuals' earnings variance. My results show that the decisions among different fields are riskier than the decisions among different types of education are. My analyses thus show the relative importance of type and field—factors that constitute the differences in educational structures—and that for the individuals, more risk inheres in the choice of the field (the decision between, e.g., business vs. health) than in the choice of type (the decision between the academic and the vocational track).

Focusing on different dimensions of educational structures thus provides important insights into how education affects outcomes of the economy and of individuals. Analyzing an educational structure that the literature had thus far not considered—tertiary vocational education—I show that institutions at the tertiary level and of the vocational type constitute an effective means to foster regional innovation. Focusing at the same time on both factors, type and field of education, which are factors that the literature had investigated separately, and analyzing their impact on an aspect that most previous studies had not considered, I show the relative importance of the type and the field of education in determining the earnings risk of individuals. This dissertation thus shows that different dimensions of educational structures are fundamental to understand how education affects the outcomes of the economy and of individuals. This dissertation furthermore shows that combining different dimensions of educational structures leads to positive outcomes for both, the economy and the individuals. The combination of sound vocational knowledge with applied research skills leads to an increase in both innovation quantity and innovation quality. For the economy, there is, therefore, no trade-off between quantity and quality. At the level of the individuals, this combination results in high returns but low risk of human capital investments. For individuals, there is therefore neither a trade-off between the profit and the risk. Moreover, the combination of different dimensions of educational structures allows the alignment of interests of the economy—increasing innovative performance through the combination of vocational knowledge and applied research skills—and of individuals—high returns to education, but low risk through UAS education. Different dimensions of educational structures—and their analysis—are thus fundamental for the economy and the society.

Chapter 2

Tertiary Vocational Education and Innovation – Quantity

Part of this chapter is an extended version of early parts of the working paper "Regional Effects of Applied Research – Universities of Applied Sciences and Innovation", by Pfister, Rinawi, Harhoff & Backes-Gellner, 2016.

2.1 Introduction

Following Jaffe's (1989) influential study on "the real effects of academic research," a study investigating the innovation effects of research in universities, a number of researchers have investigated the role played by major centers of academic research and education, such as those in Silicon Valley (CA) or on Route 128 (MA), in enhancing a country's innovation activities (e.g., Audretsch & Stephan, 1996; Mansfield & Lee, 1996, Saxenian, 2000). More recently, some studies have also successfully resolved endogeneity problems and identified causal effects (e.g., Toivanen & Väänanen, 2016; Valero & Van Reenen, 2016). However, two issues remain unresolved: First, the literature has mainly examined the effect on innovation of academic universities that predominantly focus on basic research (e.g., Rosenberg & Nelson, 1994), neglecting the impact of institutions that conduct and teach applied research. Second, regional heterogeneity in innovation activities can be very substantial. Thus what works for the major innovation centers, which often draw upon many top-ranked academic research institutions, might not work for other regions or areas of a state or country. Whether the implementation of applied education institutions can drive innovation activities in regions outside of major centers of commercial innovation remains unknown.

This paper directly tackles these two issues by investigating the effect of the establishment of applied research institutions on regional innovation activities. To do so, we exploit an educational policy intervention in Switzerland in the mid-1990s, the establishment of Universities of Applied Sciences (UAS). Because UAS were created and funded to both conduct and teach applied research, their establishment allows us to estimate the effects of applied research on innovation activities, using a difference-in-differences (DiD) methodology. According to their legal mandate, UAS must (a) focus their research and teaching on applying scientific methods and knowledge, (b) collaborate with firms when conducting their research, and (c) collaborate with other research-oriented institutions, including both academic universities and other UAS.

We study the effect of the establishment of UAS and the supply shock in applied research that it generated on regional innovation activities by using a difference-in-differences method, in which we compare treated regions (with newly established UAS) with untreated regions (with no UAS). Because this estimation technique requires that both, the treated and the untreated regions have parallel trends before the UAS establishment took place, we intensively investigate this parallel trends assumption and find strong empirical support for it. To determine whether a region is treated or untreated, we first discuss the possible mechanisms through which a UAS affects the regions' innovation activities. Second, we define the geographical area in which these mechanisms are likely to appear, using the distance and travel time from each municipality to the closest UAS.

To measure innovation effects, we use patent information because patents are the major source of information on new technologies, and are systematically screened and recorded by patent offices (Nagaoka, Motohashi, & Goto, 2010; Giuri et al., 2007). We use data from the European Patent Office (EPO), which allows us, using the location of each applicant, to determine whether a region has patent applications. In case of multiple applicants, we fractionate the patents, that is, we assign an equal share of the patent to each applicant's region. For our outcome measure of "regional patenting activity," we calculate the number of patent applications per year.

Our empirical results show an increase in the quantity of innovation activities after the establishment of UAS: Depending on the specification of our econometric model, we estimate an increase of 7.5 to 13 percent in regional patenting activity. Our large number of robustness tests verify that this quantitative innovation effect is very robust. In the last section, we provide additional empirical analyses of the mechanisms that might underlie the increased innovation activities. Our results indicate that the effects are at least partly due to a change in the labor supply, i.e., UAS graduates that spread into the treated regions after the UAS were established.

For national or regional innovation policy makers, our results suggest that the establishment of applied research and higher education institutions helps to foster regional innovation by spreading innovation activities to areas outside the major innovation centers, often through more traditional and small or medium-sized enterprises. The UAS intensify applied research and innovation in these enterprises by providing graduates who combine thorough vocational knowledge (acquired through mandatory pre-UAS apprenticeships) with applied research skills.

2.2 Institutional Background

2.2.1 The Swiss Education System and the Universities of Applied Sciences

Before the UAS reform and the resulting UAS establishment in the 1990s, the higher education system in Switzerland was essentially built upon two pillars: (a) 10 cantonal and two federal universities that together served approximately 10 percent of the country's population, and (b) professional vocational education and training institutions for approximately 15 percent of the population (also referred to as the PVET sector).[1] This situation changed structurally with the establishment of UAS, as a result of a policy reform that aimed at revitalizing and strengthening the Swiss economy.[2] The Swiss federal government's decision to establish UAS throughout the country aimed at (a) providing apprenticeship graduates from the dual vocational education and training system (VET) with a career perspective by offering them an opportunity to earn a three-year bachelor's degree in addition to their apprenticeship degree and (b) fostering regional innovation activities. To support innovation by UAS, educational policy makers designed the new institutions to conduct and teach applied research. The legal mandate of the UAS requires them to conduct and teach applied R&D and to provide related services to and collaborate with public or private sector firms. The underlying idea was that UAS should provide a steady supply of highly skilled individuals with both practical and scientific knowledge, thereby fostering the direct transfer of knowledge and technology between the research institutions and public or private sector

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[1] The Swiss education system has both an academic and a vocational track at the upper secondary and tertiary levels. Almost 25 percent of individuals, after completing nine years of compulsory schooling, follow the academic track at the upper secondary level and go to a four-year Baccalaureate School (retrieved January 2019 from https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/personen-ausbildung/sekundarstufe-II.html).

These individuals have access to both the cantonal universities and the two Federal Institutes of Technology, which are academic institutions at the tertiary level. However, most Swiss students follow the vocational track: The large majority complete an apprenticeship and combine work in a host company with lessons in a vocational school. Graduates receive a nationally recognized certificate that gives them access to vocational institutions at the tertiary level: UAS, Professional Education and Training Colleges, and (Advanced) Federal Professional Education and Training Exams (see, e.g., Swiss Coordination Centre for Research in Education (SCCRE) 2007, 2010, and 2014). Although the latter two institutions remained at the ISCED level 5B and allowed vocational graduates to acquire formal, continuous training, none of them had a legal mandate to conduct research (Bereuter, 2011; Eidgenössische Fachhochschulkommission, 2000).

[2] For further information about the reform and its implementation, see Botschaft FHSG (1994), Botschaft HFKG (2009), Federal Office for Professional Education and Technology (OPET) (2009), Bundesgesetz Fachhochschulen 1995, Bundesgesetz HFKG 2011, Eidgenössische Fachhochschulkommission (2000, 2002), Kiener (2013), Projektgruppe Bund-Kantone Hochschullandschaft 2008 (2004), or Weber and Tremel (2010).

firms that could profit from that knowledge and technology (see Staatssekretariat für Bildung, Forschung und Innovation, 2015, or Botschaft Fachhochschulgesetz, 1994).

In terms of research, UAS are thus legally required to adhere to the practical needs of Swiss firms and to focus on applied research and development projects and public services. UAS teaching therefore combines practical expertise, theoretical skills, and R&D experience. In contrast, academic universities offer basic academic research along with academic training and are expected to compete in the international scientific community. Their curricula focus on the broad foundations of the respective scientific fields and concentrate much more on theory and abstract conceptual knowledge (see, e.g., Kiener, 2013, Projektgruppe Bund-Kantone Hochschullandschaft 2008, 2004, or Botschaft Fachhochschulgesetz, 1994).

Although fields of study may overlap between universities and UAS—e.g., engineering, business administration and chemistry—and graduates may end up in almost the same occupations and jobs, their educational careers differ substantially: While students in Swiss academic universities come directly from college preparatory high schools (known as "Gymnasium" or Baccalaureate schools), UAS students usually come from an apprenticeship in the dual VET system that involves both classroom education and practical training, including work experience at the training firm. In addition, while students from both the academic university and the UAS track may study in the same field (e.g., engineering), the first group focuses on the abstract and theoretical aspects of the subject, whereas the second group focuses on the application of theoretical knowledge to the needs of firms and markets. Therefore, the second group often collaborates with local firms. The reform thus added a new type of higher education institution with a clear focus on conducting and teaching applied research to the traditional university sector, with its basic academic research and general scientific training.[3]

2.2.2 The Establishment Process of the Universities of Applied Sciences

To estimate the effect of the UAS reform on patenting activity, we exploit two sources of variation in the establishment of UAS campuses: location and time. To show that from an

[3] Both institutions are at ISECD level 5A and are considered different but of equal value.

innovation perspective, the establishment of UAS was a random result, we describe the process through which the establishment was determined.[4]

Similar to the University of California system, which comprises over 10 university campuses such as Berkeley in the north and UCLA in the south, the Swiss UAS are also a system of campuses spread out over different regions of Switzerland.[5] The UAS and their campuses were not always new institutions (greenfield institutions). Instead, they were often further developments of existing Professional Education and Training (PET) colleges (brownfield institutions) that offered education in the fields of STEM (science, technology, engineering, math), business administration, and design. These PET colleges, classified as ISCED level 5B institutions, allowed individuals with an upper secondary vocational degree to proceed to the tertiary level and enhance their managerial and technical expertise in their respective occupational fields. Starting in 1996, the PET colleges could apply for accreditation as a UAS.

However, to receive this accreditation, PET colleges had to fulfill a number of legal requirements specified by the federal government. These requirements encompassed the core characteristics of UAS: the legal mandates for teaching, services, collaboration, applied research and development. In addition, to reduce duplication, the federal government required the consolidation of a number of PET colleges and their respective programs into a single UAS. In this way, the federal government ensured the creation of UAS campuses with a sufficiently large size and a solid financial base.

The application process[6] started with an open call for applications. To ensure that the application process adhered to legal requirements, the federal government created a federal UAS commission (*Eidgenössische Fachhochschulkommission*) to evaluate the PET applications, decide on further requirements that the PET colleges needed to satisfy, control their implementation and provide support for project management. Beyond being evaluated by the federal UAS commission, the

[4] This random establishment process, which is unrelated to unobservable innovation characteristics, might be the cause for the parallel trends, which are shown in chapter 2.4 Empirical Framework, between the treatment and the control groups.

[5] The University of Applied Sciences Berne, for example, has campuses in Burgdorf, Biel, Berne, Magglingen, and Zollikofen. Those in Biel and Burgdorf provide programs in engineering & information technology and architecture, wood & civil engineering. The campus in Zollikofen specializes in agricultural, forest and food science programs, the campus in Magglingen offers sports studies, and the campus in Bern offers programs in business, health, social work and the arts.

[6] For further information about UAS accreditation and the UAS accreditation process, see Botschaft FHSG (1994), Bundesgesetz Fachhochschulen (1995), Eidgenössische Fachhochschulkommission (2000, 2002), and Kiener (2013).

applying PET colleges also had to undergo further evaluations by several other institutions, including peer reviews. The evaluation was carried out for the entire UAS, individual campuses, and even individual programs. Ultimately, the decision of whether to confer accreditation lay with the Federal Council (*Bundesrat*).

To ensure the successful implementation of the new legal mandates and to enforce the consolidation of PET colleges into individual UAS, the federal government restricted the maximum number of UAS to approximately ten. Therefore, some of the applying PET colleges had to be closed, while others had to relocate as part of a consolidation. The federal restrictions provoked heated political discussions about the location of UAS and their campuses. In particular, the requirements for consolidating UAS campuses and programs led to political trench warfare between—and even within—cantons, the political unit that carried the main financial UAS burden. Crucially, to guarantee easy access to UAS across all of Switzerland, the federal government required an equal distribution of these ten UAS throughout Switzerland. The location decisions were therefore made primarily on the basis of providing this even distribution.

After enacting the UAS law, the federal government received the first ten UAS applications. One year later, this number had already increased to fourteen, as some cantons failed to agree on intercantonal contracts and applied individually. In response to the first round of applications, the Federal Council decided to establish only seven UAS: a western one in the French-speaking part of Switzerland, a southern one in the Italian-speaking part, and five in the German-speaking part. However, the cantons strongly opposed this decision and started angry renegotiations on the appropriate number and locations of these UAS (campuses). In the end, individual cantons started forming new alliances with their neighboring cantons, trying to establish intercantonal contracts to promote their own PET colleges. The Federal Council and the federal UAS commission had to repeatedly admonish the individual PET colleges to overcome their provincialism and start cooperating across cantonal borders.

The Federal Council maintained its position and assigned a conditional accreditation to only seven UAS. The conditional accreditation included additional requirements to consolidate individual PET colleges into one UAS. In some cases, the relocations and consolidations of campuses and programs continued until 2006. We reconstruct the history of all UAS and their campuses in the German-speaking part of Switzerland, with a focus on campuses, as the federal government accredited each UAS campus individually. To reconstruct the location and the year of establishment of each UAS campus, we use information from the Swiss government reports, newspapers articles, annual reports from the UAS themselves, cantonal laws, and interim reports from institutions involved in the creation process.

To illustrate the application process in more detail, we describe the establishment of the UAS in Zurich and the UAS East, i.e., in eastern Switzerland. In 1996, eight cantons applied for accreditation as a UAS "Zurich-East." However, because the cantons could not agree on the distribution of power, their project failed, and they broke apart and instead applied for four individual UAS with campuses in the cities of Zurich, St. Gallen, Rapperswil/Wädenswil, and Chur/Samedan/Buchs. The federal UAS commission did not accept the individual applications and instead proposed the establishment of two UAS. The first, "UAS East," comprised the areas of Zurich, St. Gallen, and Rapperswil/Wädenswil. The second, "UAS South-East," comprised the areas of Chur, Samedan, and the city of Schaan in Lichtenstein. The Federal Council, in turn, accepted the establishment of only two UAS, one in Zurich and one in the eastern part of Switzerland. After the rejection, the cantons in the eastern part started to plan a UAS comprising the cities of Chur, Buchs, Rapperswil, and St. Gallen. Zurich, for its part, had already received a conditional accreditation.[7]

This example shows that the required consolidations and the resulting discussions among cantons led not only to the establishment of new campuses and the relocation and closing down of old campuses, but also to time delays in the establishment of UAS. Given that this development was highly driven by political factors, the decision of where and when a UAS campus was established was hardly foreseeable and remained open until the very end of the process—and was therefore unlikely related to innovation activities. Thus the timing and location of UAS campuses appear to be related more to political factors and all kinds of coalition building rather than to underlying differences in economic, technical, or innovative ones.

[7] The application process for the Zurich and the eastern UAS is less complex than that in other areas of Switzerland is. The Northwestern UAS, for example, included a series of applications by different and constantly changing cantons and several rejections by the federal government.

This political trench warfare included all political means possible in the Swiss democracy. In Basel, for example, members of the national parliament submitted two interpellations to prevent destructive competition between potential UAS campuses and required the creation of more than one UAS in the northwestern area. In Geneva, citizens even voted on—but voted down—on a popular petition that should prevent the consolidation of UAS campuses in their canton.

2.2.3 UAS Campuses, their Location, and their Year of Establishment

This section summarizes the establishment and consolidation process of each campus of the UAS of Eastern Switzerland, Zurich, Central Switzerland, Bern, and Northwestern Switzerland. We thereby focus on the campuses in engineering, IT, chemistry, and the life sciences, describing where they are (and were) located, when they opened their door, when they established the legal (inter)cantonal basis to manage the UAS, and—in the case of consolidation due to the requirements imposed by the UAS commission and the Federal Council—where they concentrated their campuses.[8] Our analysis relies on, among other types of information, reports and laws by governmental institutions, such as the Federal Council or the UAS commission, articles from local newspapers, and interim reports.[9] Table 1 summarizes this establishment and consolidation process of all five UAS and their campuses, located in the German-speaking area of Switzerland and their respective campuses in engineering, IT, chemistry and the life sciences.

Table 1 The UAS, the location of their campuses, and the year of establishment

University of Applied Sciences	Location of Campuses	Year of establishment
Bern University of Applied Sciences	Bern	1997-2003
	Burgdorf	1997
	Biel	1997
University of Applied Sciences of Eastern Switzerland	St. Gallen	2000
	Rapperswil	2001
	Buchs	2001
	Chur	2000
University of Applied Scineces of Zurich	Winterthur	1998
	Wädenswil	1998
	Zürich	1998
University of Applied Sciences of Central Switzerland	Horw	1997
University of Applied Sciences of Northwestern Switzerland	Oensingen	1998-2003
	Olten	2003-2006
	Brugg-Windisch	1998
	Muttenz	1997

Source: Authors' illustration, based on Botschaft FHSG (1994), Bundesgesetz Fachhochschulen (1995), Eidgenössische Fachhochschulkommission (2000, 2002), Kiener (2013), articles from local newspapers, and interim reports.

[8] Other campuses—such as those in business administration, social work, or arts—are only included in the description if they affect the establishment process of the campuses in engineering, IT, chemistry, and the life sciences (see, for example, the following example of the campus in Bern).

[9] For each UAS campus, we list a number of selected sources giving a good overview of the establishment process.

Bern UAS

In 1997, the Federal Council conferred a conditional accreditation to the UAS Bern and its engineering and IT campuses located in Biel, Bern and Burgdorf.[10] While the first evaluation report of the UAS commission in 2000 showed that the UAS Bern already fulfilled a large part of the requirements, the commission required—among other requirements—a stronger focus of the engineering and IT programs and their concentration (Eidgenössische Fachhochschulkommission, 2000). The UAS Bern therefore reorganized their campuses to ensure an efficient managerial and organizational structure and, consequently, an efficient use of resources. This reorganization caused the fusion of engineering and IT in Bern, Burgdorf and Biel. While engineering and IT programs moved away from the city of Bern, study programs in business administration, social works, and arts were concentrated in this city.

A large number of political and UAS representatives tried to counteract these concentration plans. They emphasized the economic importance of Bern, arguing that the city of Bern produced 52 percent of the cantonal gross domestic product; in addition, 85 percent of the telematics and 72 percent of the medical industry in the canton of Bern are located in the city of Bern (Kiefer, 2001).[11] Despite this resistance, the engineering and IT departments in Bern had to close their doors and moved to Burgdorf and Biel in 2003.

Table 2 The UAS of Bern and of Central Switzerland, the location of their campuses, and the year of establishment

University of Applied Sciences	**Location of Campuses**	**Year of establishment**
Bern University of Applied Sciences	Bern	1997-2003
	Burgdorf	1997
	Biel	1997
University of Applied Sciences of Central Switzerland	Horw	1997

Source: Authors' illustration, based on Botschaft FHSG (1994), Bundesgesetz Fachhochschulen (1995), Eidgenössische Fachhochschulkommission (EFHK) (2000, 2002), Kiener (2013), articles from local newspapers, and interim reports.

[10] For an overview of the establishment process of the UAS Bern, see, e.g., Kiefer (2001); Berner Zeitung (2003), Arbenz and Gmuer (2003).

[11] Supporters of the fusion process, e.g. the president of the regional trading and industry association, argued that ensuring the future quality of the UAS was more important than the location decision (Kiefer, 2001).

UAS of Central Switzerland

The UAS of Central Switzerland unified eight different PET colleges and was the only UAS in Switzerland whose campuses did not provoke heated debates; all campuses were located in Lucerne and Horw, a suburban municipality of Lucerne.[12] The Federal Council conferred a conditional accreditation to the Central UAS—including the engineering and IT campus in Horw—in 1997. The UAS commission stated in the reports of 2000 and 2002 that the Central UAS either already fulfilled the requirements for acquiring the final accreditation or implementation of these requirements was at a very advanced level (Eidgenössische Fachhochschulkommission, 2000, 2002).

UAS of Eastern Switzerland

While the establishment process of the UAS of Central Switzerland was rather simple, that of the UAS of Eastern Switzerland was much more complicated (see 2.2.2 The Establishment Process of the Universities of Applied Sciences).[13] Although the Federal Council conferred a conditional accreditation to the campuses in St. Gallen, Chur, Buchs and Rapperswil in the late nineties, the UAS commission emphasized that the Federal Council was going to refuse a final accreditation in 2003 if the Eastern UAS would not fulfill a number of fundamental requirements (Eidgenössische Fachhochschulkommission, 2000). Amongst others, the UAS commission criticized the Eastern UAS for its late start in establishing an organizational structure and a legal basis[14]. In addition, the commission required a common strategy for the Eastern UAS, more collaboration among the campuses, the reduction and the concentration of programs, and a clear focus for research and teaching. A *conditio sine qua non* was the fusion of campuses in St. Gallen and in Chur[15] (which took place in 2000), and the strategic and operative integration of Rapperswil into the Eastern UAS (taking place in 2001).

12 For further information about the establishment of the UAS of Central Switzerland, see, e.g., Haessig (1996) or Merki (1998).

13 For further information about the establishment of the campuses of the UAS of Eastern Switzerland, see, e.g., Stahlberger (1999), Eberhard (2000), St. Galler Tagblatt (2003, 2006), Neue Zürcher Zeitung (2006).

14 The intercantonal contracts for the campuses in Chur and in St. Gallen were ratified in 2000, and those for the campuses in Rapperswil and Buchs in 2001 (Bereuter, 2011).

15 In St. Gallen, the departments for engineering and IT, business administration, and social work fused; in Chur, those for engineering and IT and business administration fused.

Table 3 The UAS of Eastern Switzerland, the location of its campuses, and the year of establishment

University of Applied Sciences	Location of Campuses	Year of establishment
University of Applied Sciences of Eastern Switzerland	St. Gallen	2000
	Rapperswil	2001
	Buchs	2001
	Chur	2000

Source: Authors' illustration, based on Botschaft FHSG (1994), Bundesgesetz Fachhochschulen (1995), Eidgenössische Fachhochschulkommission (2000, 2002), Kiener (2013), articles from local newspapers, and interim reports.

In 2002, the UAS commission argued that the Eastern UAS had fulfilled most of the requirements (although their implementation was still in progress) and underlined the importance of the fusions in Chur and St. Gallen, as well as the embedment of Rapperswil into the UAS of Eastern Switzerland (Eidgenössische Fachhochschulkommission, 2002). Given the complicated political process for establishing an intercantonal contract and the large number of fundamental requirements imposed by the UAS commission, we consider these fusions as the beginning of the Eastern UAS campuses.[16]

UAS of Zurich

The UAS Zurich[17], the result of the fusion of eight former PET colleges, was conditionally accredited in 1998. Although the UAS Zurich followed a "campus strategy" from the start—their campuses were and remain located in Zurich, Wädenswil and Wintethur—the UAS commission criticized the UAS' unsatisfactory holding structure, i.e., the lack of a concerted strategy, managerial structure, integration, and focus. In the reorganizational process, in which the UAS Zurich introduced—amongst others—a new department structure, the research and teaching profiles of the campuses became clearer: Wädenswil thereby became a competence center for chemistry and the life sciences and Winterthur for engineering and IT. The location of the campuses, though, remained unchanged.

[16] In the annual report of 2003, the principal of the campus in Chur confirms our historical reconstruction, stating that the beginning of the campus in Chur was much later than the conditional accreditation in the late nineties (Hochschule für Technik und Wirtschaft Chur, 2004)

[17] For an overview of the establishment process of the UAS Zurich, see Bereuter (2011), Hagenbüchle (1997), Neue Zürcher Zeitung (1995, 1997, 1998a, 1998b, 1998c).

Table 4 The UAS of Zurich and of Northwestern Switzerland, the location of its campuses, and the year of establishment

University of Applied Sciences	Location of Campuses	Year of establishment
University of Applied Scineces of Zurich	Winterthur	1998
	Wädenswil	1998
	Zürich	1998
University of Applied Sciences of Northwestern Switzerland	Oensingen	1998-2003
	Olten	2003-2006
	Brugg-Windisch	1998
	Muttenz	1997

Source: Authors' illustration, based on Botschaft FHSG (1994), Bundesgesetz Fachhochschulen (1995), Eidgenössische Fachhochschulkommission (2000, 2002), Kiener (2013), articles from local newspapers, and interim reports.

UAS of Northwestern Switzerland

In the report of 2000, the UAS commission stated that although moving into a desirable direction and showing positive dynamics, the establishment of the UAS of Northwestern Switzerland was a very problematic case (Eidgenössische Fachhochschulkommission, 2000: 65).[18] The establishment was difficult and complex because four cantons applied for the Northwestern UAS—Basel (Baselland and Baselstadt), Aargau and Solothurn—and all cantons wanted to integrate their PET colleges into the new UAS. In 1996, each of the four cantons therefore submitted an individual application involving the following locations of PET colleges in engineering, IT, chemistry, and the life siences: Muttenz (Baselland and Baselstadt), Oensingen (Solothurn), and Brugg-Windisch (Aargau).

Although conferring a conditional accreditation to these campuses in 1997 and 1998, the Federal Council (and the UAS commission) criticized the missing concerted strategy and its underlying provincialism and clearly communicated that only one UAS would be accepted in the Northwestern area of Switzerland. The Federal Council thus rejected the establishment of three individual UAS and required a new strategy that included the concentration of programs and campuses (Eidgenössische Fachhochschulkommission 2000, 2002).

In the following years, each of the three cantons tried to bring the UAS into their region, forming alliances and promoting their campuses. One part of the canton of Aargau proposed a UAS campus

[18] For an overview of the establishment process of the UAS of Northwestern Switzerland, see, e.g., Aargauer Zeitung (2003), Basler Zeitung (1998, 1999a, 1999b, 2000), Berner Zeitung (2005), Kiefer (1997, 1999a, 1999b, 2001), Flückiger (2004), Frey (2001), Oltner Tagblatt (2003), Solothurner Zeitung (2005, 2008).

in engineering, IT, chemistry and the life sciences in Brugg-Windisch. The other part of the canton of Aargau collaborated with Solothurn and planned to concentrate the campuses in the cities of Aarau and Olten. To corroborate the Aarau-Olten solution, the engineering and IT campus in Solothurn relocated from Oensingen to Olten in 2003.

The proximity of the project Aarau-Olten would have been a threat for a potential UAS concentration in Basel. Basel, therefore, applied for a campus for IT and the Arts. Although the campus for IT was rejected, the campus for Arts was conferred accreditation and thus weakened the project Aarau-Olten. Due to the concentration of the Arts in Basel, and—amongst others—the heated debate within canton of Aargau, the project Aarau-Olten failed.[19]

After the repeated criticism of the Federal Council and the UAS commission, the three cantons finally signed an intercantonal agreement to reassess the duplications in programs and campuses: Muttenz gained the campus in chemistry and the life sciences; Brugg-Windisch gained the campus in engineering and IT. While Olten's engineering and IT department moved to Brugg-Windisch in 2006, the city received the campuses in applied psychology, social work, and business administration.

[19] The appendix of this chapter shows how patent applications developed in Oensingen and in Olten before and after the relocation of their campus, providing insights into how the region reacted on a campus opening and closing its doors.

2.3 Data

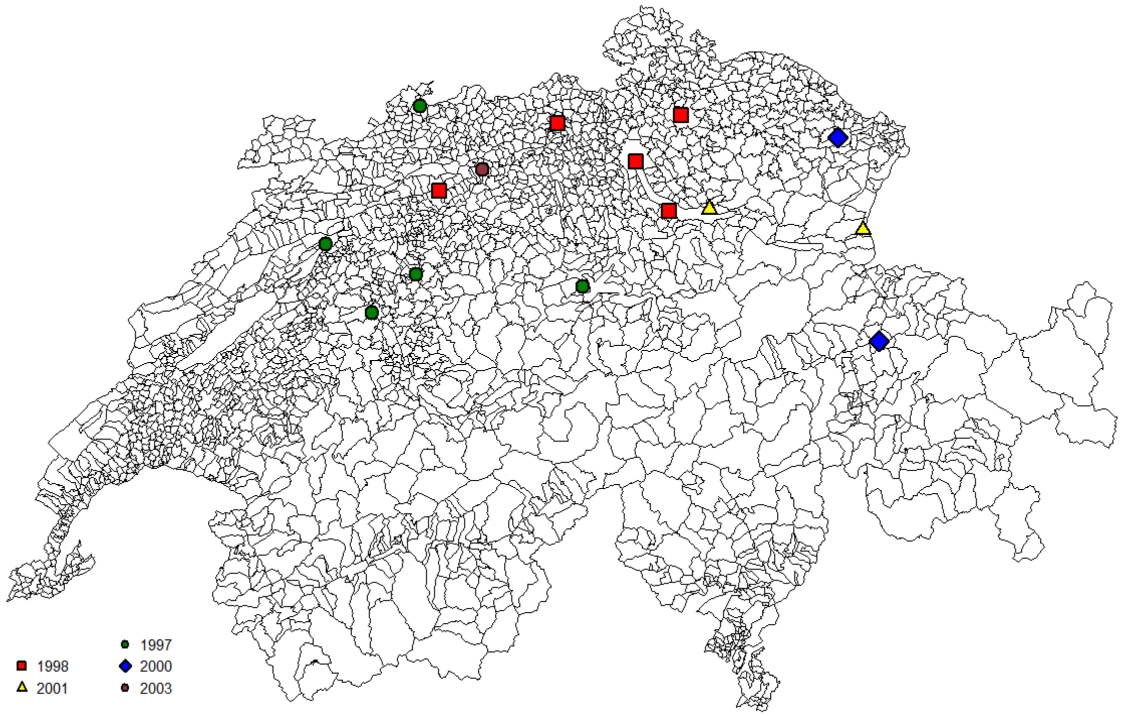
2.3.1 Definition of Treatment and Control Groups

The establishment of UAS was staggered, with the first campuses opening in 1997 and the last in 2003. For our analysis, we use the establishment of all UAS campuses with programs in engineering, IT, chemistry, and the life sciences. We focus on these particular fields because they are the most likely to have an effect on innovation as measured by patents.[20] Moreover, these fields have been used in previous studies on similar topics (e.g., Toivanen & Väänänen, 2016; Schartinger, Rammer, Fischer, & Fröhlich, 2002). We restrict our analysis to campuses located in the German-speaking part of Switzerland, because we were able to clearly identify a precise starting date for the applied research and teaching only for the German-speaking part of the country.[21] However, the German-speaking UAS constitute two-thirds of the UAS in Switzerland. Figure 1 shows the 15 UAS campuses that were newly established between 1997 and 2003.

[20] We thus exclude UAS, for example, in the fields of social work, arts, and music, assuming that the innovations they produce—such as social innovations or innovative art and music—cannot be well measured by patents.

[21] Due to insufficient documentation and additional language and terminology issues, we are able to clearly identify an exact start date for the UAS only in the German-speaking parts (and, thus far, not in the French or Italian-speaking parts).

Figure 1 UAS campuses



Source: Authors' calculations, based on Grenzen 2016, SFSO GEOSTAT / swisstopo and on SFSO GEOSTAT, 2007.

Our definition whether a municipality was treated or untreated by the UAS reform builds on a commonly accepted finding in innovation and in urban economics: Knowledge spillovers and innovation are spatially concentrated and geographically localized (Feldman & Kogler, 2010; Moretti, 2011). A sizable and growing literature stream within these fields investigates the role of universities in generating and fostering such regional innovation clusters (Bonander et al., 2016; Drucker & Goldstein, 2007; Liu, 2015). This literature suggests that universities affect regional innovation (and other economic outcomes such as productivity, growth and entrepreneurial activity) not only by producing (basic) research, but also by generating direct and indirect spillovers (Liu 2015): Direct spillovers result from the interaction between universities and firms, and from graduates entering the local labor market, remaining in it, and enhancing its quality. Indirect spillovers arise due to agglomeration economies, i.e., benefits or increasing returns due to resources located nearby, such as firms or skilled people (Feldman & Audretsch 1998; Glaeser, 2010).

Both types of spillovers are sensitive to geographical distance, as proximity implies lower costs (Feldman & Kogler, 2010; Moretti, 2011). Moreover, tacit knowledge—a fundamental driver of these spillovers—is regionally embedded (Feldman & Kogler, 2010; Lundvall & Johnson, 1994; Maskell & Malmberg, 1999). Given the non-codifiable nature of tacit knowledge, its transfer therefore requires "face-to-face exchange, routines, habits and norms, conventions of communication and interaction" (Feldman & Kogler 2010: 389).[22] This sensitivity to distance implies that the effect of a UAS campus on the economy is geographically limited. We are therefore able to identify this local effect by defining the area of influence of a UAS campus, its catchment area.

To define this UAS catchment area, we focus on the first form of direct spillovers, UAS graduates. UAS graduates are highly skilled individuals entering the labor market, remaining in it, and enhancing its quality. They enhance the quality of the labor market because they possess a new type of human capital that includes vocational and academic education and that particularly focuses on applied research and development and on the transfer of scientific knowledge into practice. Assuming that these UAS graduates have a stable mobility behavior, we are able to localize their effect on regional innovation. Such stable mobility behavior involves two aspects: (a) potential UAS students study at a UAS campus nearby, and (b) UAS graduates stay in the area in which they have completed their studies. Chapter 2.6 Robustness Checks analyzes the question of potential contamination due to different forms of mobility of UAS graduates and shows that UAS graduates exhibit a very low level of mobility. The assumption of stable mobility behavior is therefore very plausible.[23]

The stable mobility behavior of UAS graduates thus allows us to measure the local effect of a UAS campus. To limit the area in which such a local effect appears, we focus on the distance between the place where UAS graduates live and the place where they work. In other words, we

[22] Carlino et al. (2007) review, amongst others, the studies by Andersson, Burgess, and Lane (2007), Anselin, Varga, and Acs (1997), Audretsch and Feldman (1996), Jaffe, Trajtenberg, and Henderson (1993), and Rosenthal and Strange (2001), and conclude that spillovers are highly localized, i.e., at the zip code level or within metropolitan areas.

[23] The large majority of UAS graduates continues living in the same area in which they have graduated five years ago (see 2.6 Robustness Checks).

Moving behavior of potential UAS students—i.e., upper secondary education graduates who consider a study at a UAS—is likely to be even lower: Previous regional studies using Swiss data show that young adults exhibit a very low level of mobility (e.g., Muehlemann, Ryan & Wolter, 2013; Muehlemann & Wolter, 2011). Thus contamination due to potential UAS students moving from the control group to the treatment group is very unlikely.

In addition, students' commuting behavior is more localized than that of workers. In other words, commuting distances to an educational institution are shorter than commuting distances to the workplace (SFSO/ARE, 2002, 2007). Contamination due to UAS students commuting to a UAS campus from the control to the treatment group is therefore very unlikely, too.

define the optimal size of a UAS catchment area following previous regional studies[24] and focusing on commuting patterns of individuals living in Switzerland, i.e., travel distance, travel time, and typical commuting behavior. The city in which the campus is located thereby constitutes the center of the catchment area.[25] The appropriate distance from the UAS campus to the border of the catchment area is based on empirical evidence of commuting patterns of individuals living in that area, from the mobility and transport microcensus (SFSO/ARE, 2007). This representative survey shows the typical commuting behavior in 2005: almost 90 percent of employed individuals living in Switzerland commute less than 25 kilometers (approximately 15 miles); of these individuals, 90 percent have a commute of no more than 45 minutes.[26] We therefore define a municipality as a "treated region" if it is located within 25 kilometers of a UAS campus.[27]

Because a linear distance measure may be distorted given the unique Swiss topography with all of its lakes and mountains, we use the actual travel distance as measured by geo-statistical data (SFSO, GEOSTAT 2007). These data provide information on the actual travel distance (in car kilometers) rather than the linear distance between all Swiss municipalities. Figure 2 shows the catchment area for the UAS campus in St. Gallen as an example.

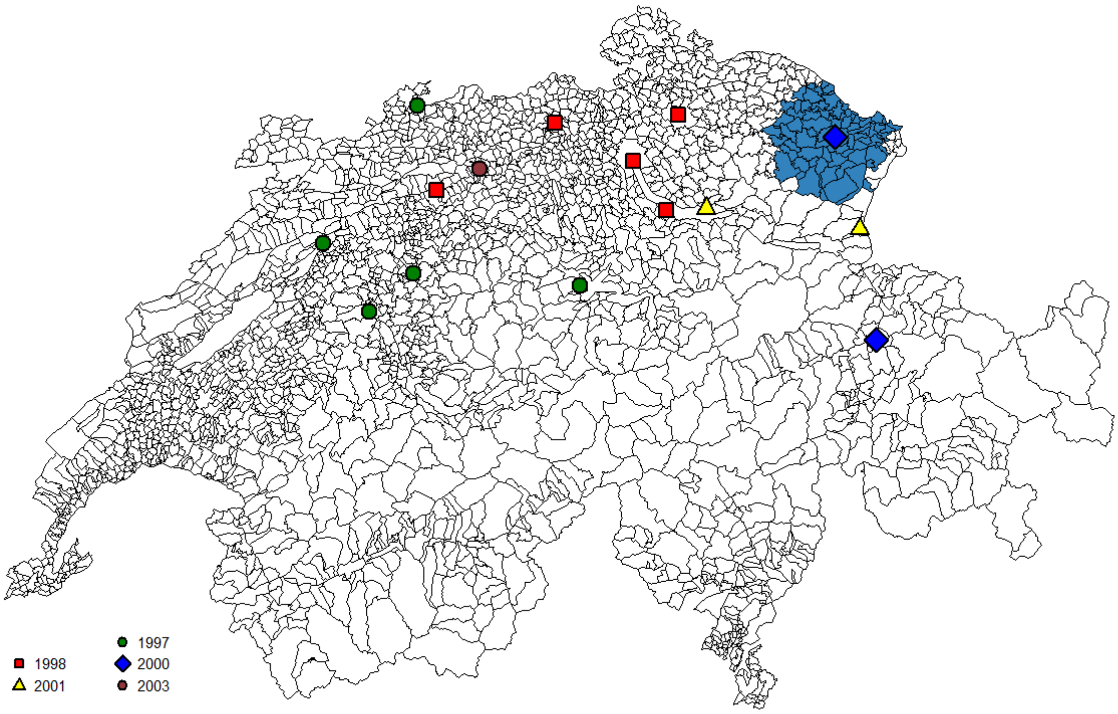
[24] For Switzerland, Muehlemannn, Ryan and Wolter (2013) and Muehlemann and Wolter (2011) specify local labor markets using commuting information. They argue that political borders are inappropriate for defining a region of economic activity in Switzerland because cantons – the largest political level – are too small. In addition, calculating travel distances using coordinates is misleading due to Switzerland's numerous mountains and lakes. They therefore calculate travel times using route guidance systems for cars from the 67 largest Swiss cities and towns to the surrounding municipalities. Their travel limit, which relies on Swiss census information from 2000, equals 30 minutes.

[25] Chapter 2.6 Robustness Checks furthermore analyzes the potential contamination due to UAS graduates commuting not to the center of the catchment area, but to another direction. The results show that such contamination does not affect our results.

[26] We use a representative survey that concentrates on to the end of our observation period because commuting behavior increased between 1990 and 2008: In 1990, 96 percent of employed individuals living in Switzerland had a commute of 25 kilometers or less, and 94 percent a commute of 45 minutes or less (SFSO 1997).

[27] If a municipality is located within two UAS catchment areas, it is classified with the closest UAS campus.

Figure 2 Catchment area for the campus in St. Gallen

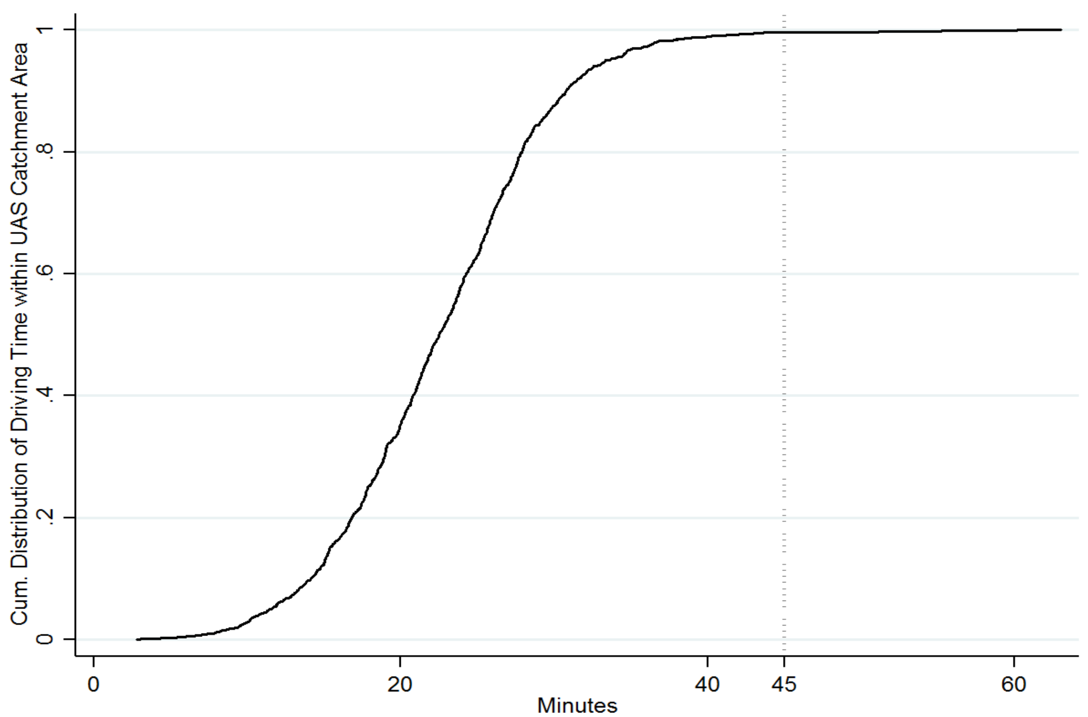


Source: Authors' calculations, based on Grenzen 2016, SFSO GEOSTAT / swisstopo and on SFSO GEOSTAT, 2007.

To test the robustness of our measure, we use "travel time," which we calculate using the respective Google application programming interface[28]: using Google, we obtain the travel time by car from each UAS campus to all Swiss municipalities. Figure 3 shows the distribution of travel time for the 25-kilometer travel distance area. The distribution shows that traveling from the most remote municipality to a UAS campus takes no more than 45 minutes. Thus when we compare the statistics for travel distance and travel time, the UAS catchment area well represents the region in which 90 percent of Swiss people would regularly commute and in which they would thus suddenly have the option of reaching a UAS after previously never having that option.

[28] Belenzon and Schankerman (2013) used Google Maps to calculate their geographic distance measures.

Figure 3 Cumulative distribution of driving time within UAS catchment area



Source: Authors' calculations, based on Google. The vertical line shows that 99.7 percent of the municipalities within a UAS catchment area are located within 45 minutes of a UAS campus.

This definition of the UAS catchment area implies that we compare the treatment group, i.e., the "treated regions" consisting of all municipalities within a 25-kilometer radius around a UAS campus, with the control group, the "untreated regions" comprising all other regions. Given that we rely on empirical evidence of commuting behavior, we measure the effect of the first form of direct spillovers explained in this section: Highly skilled UAS graduates entering the labor market, remaining in it, and enhancing its quality.

This definition of the UAS catchment area might also measure the second form of direct spillovers (interaction between UAS and firms) and indirect spillovers (agglomeration economies), because these forms of spillovers appear, like the first form, locally (Liu 2015). However, disentangling the different spillovers is difficult and beyond the scope of this dissertation. As an example, whether interaction between UAS and firms are sensitive to distance remains unclear. As the exploitation rights of inventions generated by such interaction are not regulated, collaboration between UAS and firms does not appear in the patent database.[29] Consequently, calculating the distance between UAS and firms is not possible.

Nevertheless, we try to investigate these different spillovers separately: In chapter 2.6.4 Confounding Effects: Education Expansion of Academic Universities, we focus on UAS graduates entering the labor market and show that a large part of the innovation effect is related to these graduates. However, a substantial share of the innovation effect remains unexplained and is therefore not attributable to this type of direct spillovers. Collaboration between UAS and firms, and agglomeration economies might therefore constitute further important spillovers of UAS. In the third chapter, we additionally focus on indirect spillovers: Using a subsample of first-time inventors, which include newly founded firms, we estimate the effect of UAS on a proxy for regional entrepreneurial activities.

[29] UAS might not appear in the patent database as a firm's collaboration partner because many of them do not pursue a patent portfolio strategy. Thus while academic universities and federal institutes of technology never assign the complete intellectual property rights to the cooperating firm, a large share of UAS does (Hotz-Hart, 2009).

2.3.2 Patent Data

To measure patenting activity, we use patent data from the "Worldwide Patent Statistical Database – April 2013 Version" from the European Patent Office (EPO). The EPO database, containing more than one million patent applications from 1888 to 2013, provides information about the application date and the inventors' and applicants' names, affiliations, and addresses. To localize a patent's geographic origin, we use the applicant's address. We assign each patent application to its applicant's municipality, Switzerland's smallest political unit.[30] Because almost 99 percent of all patent applications have only one applicant, they can be clearly attributed to one specific municipality. For the remaining one percent with multiple applicants from several municipalities, we fractionate the patent, i.e., we weight the number of applicants in a particular municipality by its relative number of applicants.

To construct our outcome variable "regional patenting activity," we add up the numbers of patent applications for each year and for all municipalities in a treated region and an untreated region. We choose 1990 as our first year of observation, because the creation of the UAS started in 1997, and we want to ensure a sufficiently long pre-treatment period for testing the common trends assumption. We end our observation period in 2008 because in that year, some UAS started to introduce Master's level programs, possibly causing additional effects on patenting activity and thereby possibly creating systematic biases across UAS. Our final sample contains information on more than 300,000 patent applications. Table 5 provides descriptive statistics for the regional patent quantity measure for our treated and untreated regions before and after the establishment of UAS.

[30] Switzerland comprises approximately 2,300 municipalities, 148 districts and 26 cantons, which are similar to U.S. states (https://www.bfs.admin.ch/bfs/de/home/statistiken/querschnittsthemen/raeumliche-analysen/raeumliche-gliederungen.html; retrieved January 2019).

Each municipality generally includes several ZIP codes. Overall, Switzerland has approximately 3,500 ZIP codes.

Table 5 Descriptive statistics number of patent applications

		Untreated regions				Treated regions			
	Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Before the UAS establishment	Number of Patent Applications per Municipality	2.09	13.60	0.00	270.50	7.74	99.02	0.00	4102.32
	Average Trend	1.01% (3.89)				1.36% (0.30)			
After the UAS establishment	Number of Patent Applications per Municipality	3.17	25.78	0.00	556.00	14.41	171.05	0.00	6750.17
	Average Trend	0.00% (0.30)				1.04% (0.24)			
	Number of Municipalities	392				1043			

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Given that the distribution of patent applications is skewed to the right, we transform the outcome variable to receive approximate normal distributions. A regression of the variable ln(number of patents) on the continuous year variable (1990 to 1997 for the period before the reform and 1998 to 2008 for the period after the reform) provides the average changes in the outcome variable for the treatment and the control groups and for the periods before and after the reform. The trends of the treatment and the control groups before the reform do not show a statistically significant difference, while they differ at the one percent level after the reform.

2.4 Empirical Framework

2.4.1 Difference-in-Differences Estimation

To analyze the effect of the establishment of UAS on regional patenting activity, we use a difference-in-differences approach and estimate the following equation:

Equation 1 $$ln(Number\ of\ patents_{jt+3}) = \alpha + \beta Treatment_{jt} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

The variable $ln(Number\ of\ patents_{jt+3})$ refers to the natural logarithm[31] of the number of patent applications three years after the establishment of a UAS campus ($t+3$) in municipality j. We use a time lag of three years because we assume that UAS have no immediate impact on innovation, given that potential channels for innovation take time to evolve[32].

The variable TG_j in Equation 1 is a dummy that indicates whether a municipality belongs to the treatment group, i.e., whether municipality j received a UAS campus between 1997 and 2008. The variable γ includes year dummies and shows the common time trend of the treatment and the control groups. To control for unobservable time-constant effects on the district level, we include the variable λ_k, which comprises district dummies.[33] Finally, ε_{jt} is the error term.

Our main variable of interest, $Treatment_{jt}$, is a dummy variable indicating whether municipality j has a UAS campus in year t. The coefficient β in the equations shows the effect of UAS establishment on a region's patent activity, assuming that the treated regions would have had the same trends as the untreated regions had the policy reform not happened. We test this assumption (and others) in the following.

[31] To transform the variable *Number of patents*, we add a constant of 1 to all regions.

[32] Such direct and indirect channels could be, e.g., UAS graduates or joint research projects between UAS and firms. Acquiring a Bachelor degree at a UAS takes three years, and establishing research cooperation and finishing a typical project generally takes at least three years. Although we know that many of the processes may take longer and innovation effects may become stronger over time, we use a delay of three years. Using a rather short time lag only makes our test stronger and underestimates the effect size.

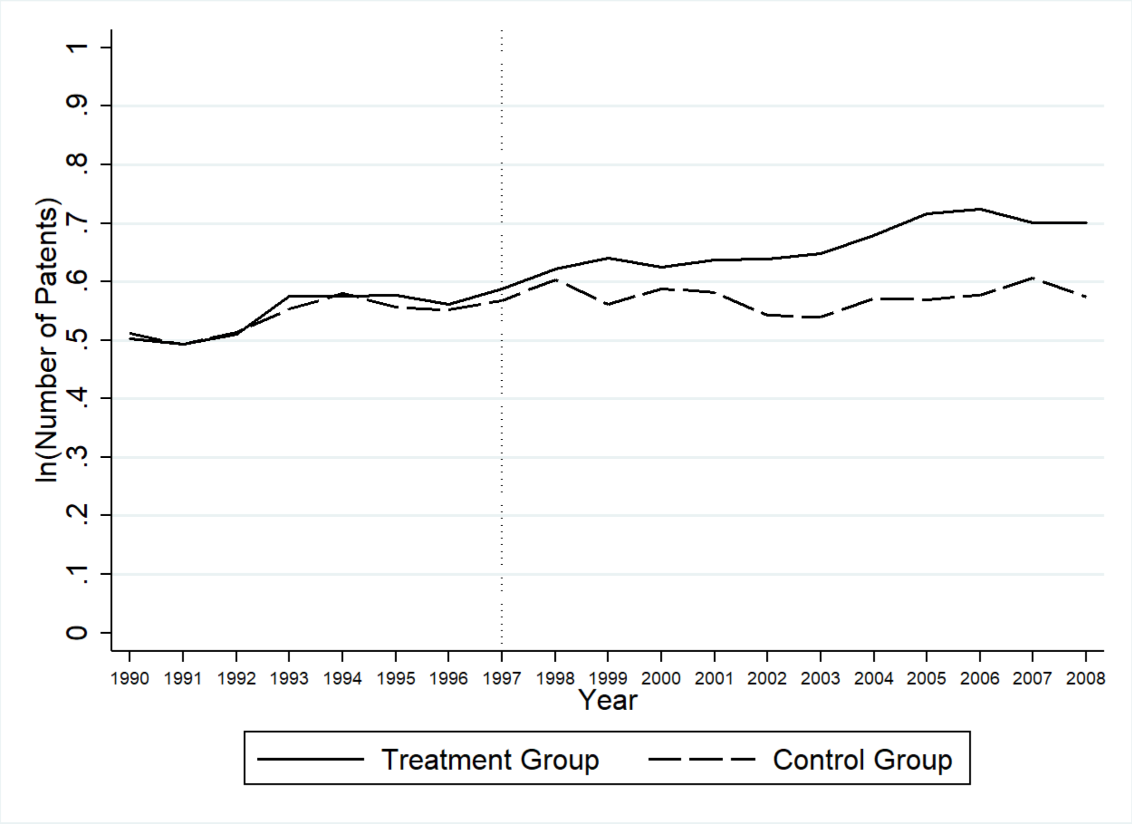
[33] We control for districts because they could potentially affect the results as follows: Although unrelated to UAS establishment, the economic background of a region—such as the industry structure or the tax regime—may have an effect on our innovation outcomes. To control for differences in economic background even in the absence of a full set of observable or even unobservable characteristics, we include a dummy variable for all of the single districts that we have in our regions.

2.4.2 Identification

The key assumption in estimating the effect of UAS in the difference-in-differences model is the parallel trends assumption: that treated regions (the treatment group) and untreated regions (the control group) have parallel trends in the absence of the UAS reform. Because our data contain information on multiple years before and after the creation of UAS, we can investigate this parallel trends assumption.

Figure 4 shows the natural logarithm of the number of patents per municipality from 1990 to 2008 for the treatment and the control groups. The curves show a common underlying trend before the establishment of UAS campuses in 1997. After the establishment, a deviation of this common trend takes place.

Figure 4 ln(Number of Patents) for treatment and control group, before and after the UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

To test whether the trends of the treatment and the control groups are parallel before the UAS establishment, or whether they show a statistically significant difference, we proceed as follows: We regress the log of the number of patents per municipality on the years 1990 to 1997, the period preceding the UAS creation. We thereby differentiate between the pre-treatment trend for the control group (the variable *Year* in Table 6 and Table 7) and the pre-treatment trend for the treatment group (the variable *Year x TG*). If the interaction *Year x TG* shows a statistically significant effect, the treatment group would have a significantly different trend than the control group.[34] While Table 6 shows the results with a linear time trend, Table 7 shows the same results for possible non-linear trends by including dummies for each year. Both tables show no statistically significant difference in pre-treatment trends (variable *Year x TG)* between the treatment and control groups.[35] Therefore, we find no indication of a violation of the parallel trends assumption.[36]

The second key assumption of our empirical strategy concerns the mobility of graduates. To estimate the unbiased effect of UAS on regional patenting activities, we assume that UAS graduates have a stable mobility and commuting behavior.[37] However, although we showed that 90 percent of employed individuals commute less than 25 kilometers to work, the remaining ten percent may commute from a non-treated area into a treated area and vice versa. In addition, graduates might still live in the catchment area in which they graduated, but commute to a firm located in the non-treated region. Moreover, after finishing their studies, UAS graduates could move from a treated to a non-treated area and start working there. Such contamination of treatment and control groups could lead to bias. Although such movement works against our hypothesis and thus makes our test stronger, we nevertheless provide a detailed analysis of the possible contamination effects in chapter 2.6 Robustness Checks and show that these effects are very small and negligible.

[34] The variable *TG* shows the difference in the log of the number of patents between the treatment and the control groups in 1990.

[35] The results of the joint F-test for the interaction between the year dummies and the variable *TG* equals 0.9393 (Prob. > F). We thus find no statistically significant indication for a difference in the nonlinear trends between the treatment and the control groups.

[36] One explanation for these parallel trends between the treatment and the control groups are the political environment and the multiple and coalition building processes of the establishment of the different UAS campuses summarized in chapter 2.2 Institutional Background.

[37] The second form of direct spillovers, interaction between UAS and firms, as well as indirect spillovers are less prone to these mobility concerns, because UAS, firms and cities are less mobile than graduates.

Table 6 Parallel trends assumption – linear trends

	Dependent Variable ln(Number of Patents)
Year	0.0101***
	(0.0039)
Year x TG_j	0.0035
	(0.0049)
TG_j	0.2396***
	(0.0462)
Constant	0.2606***
	(0.0350)
AR2	0.0131
R2	0.0134
n	11480
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table 7 Parallel trends assumption – year dummies

		Dependent Variable ln(Number of Patents)
Year		
	1990	Base Group
	1991	-0.0185
		(0.0225)
	1992	0.0026
		(0.0250)
	1993	0.0421
		(0.0290)
	1994	0.0691**
		(0.0323)
	1995	0.0461*
		(0.0271)
	1996	0.0403
		(0.0290)
	1997	0.0569*
		(0.0315)
Year x TG_j		
	1990	Base Group
	1991	0.0092
		(0.0292)
	1992	0.0060
		(0.0318)
	1993	0.0319
		(0.0355)
	1994	0.0039
		(0.0388)
	1995	0.0287
		(0.0351)
	1996	0.0189
		(0.0369)
	1997	0.0289
		(0.0391)
TG_j		0.2358***
		(0.0499)
Constant		0.2662***
		(0.0383)
AR2		0.0124
R2		0.0137
n		11480
p-Value		0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

2.5 Results

To estimate the effect of UAS on regional patenting activity, we estimate Equation 1 using the DiD estimation. Table 8 shows the results of the estimation: The $Treatment_{jt}$ coefficient equals 12.23 (13.0 percent) and is statistically significant at the one percent level. The UAS establishment thus led to a significant and economically important increase in innovation quantity.

Table 8 OLS results for patent quantity

	Dependent Variable ln(Number of Patents)
Year	yes
TG_j	0.0718 (0.0706)
$Treatment_{jt}$	0.1223*** (0.0266)
Constant	0.4507*** (0.0546)
AR2	0.2513
R2	0.2551
n	22960
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

2.6 Robustness Checks

2.6.1 Contamination of Treatment and Control Groups

In a first robustness check, we tackle the potential bias arising from contamination of the treatment and the control groups. Direct spillovers through UAS graduates potentially cause contamination, as UAS graduates who are mobile contaminate our treatment and our control groups.[38] We therefore investigate the mobility of UAS graduates, focusing on three important forms: First, we analyze whether the definition of our UAS catchment area, representing the area in which 90 percent—and not 100 percent—of individuals regularly commute, leads to contamination. Second, we analyze the mobility of UAS graduates in terms of moving behavior, i.e., UAS graduates who change their residence. Third, we focus UAS graduates not changing their residence, but commuting from a UAS catchment area into untreated regions or into a neighboring UAS catchment area.

The first form of mobility that may cause problems is UAS graduates' commuting behavior across the regional boundaries that we defined. Given the definition of our UAS catchment area, a small fraction of individuals who should be in the treatment group could be in the control group (and vice versa). Consequently, the treatment and control groups might be contaminated, particularly in the outer limits of the catchment area. To reduce this potential contamination, we redefine our catchment areas and exclude a belt of municipalities located just at the boundaries of our regions. Specifically, we now define municipalities located within 20 kilometers (instead of 25) of a UAS campus as in the treatment group and municipalities located more than 25 kilometers from a UAS campus as in the control group. Thus by keeping the treatment and control groups as clean as possible, we exclude all municipalities within a distance of between 20 and 25 km to a UAS campus from our analysis. In other words, we exclude the outer limits of our original area from the analysis because those are the areas where the treatment and control groups could most likely be contaminated in both directions.

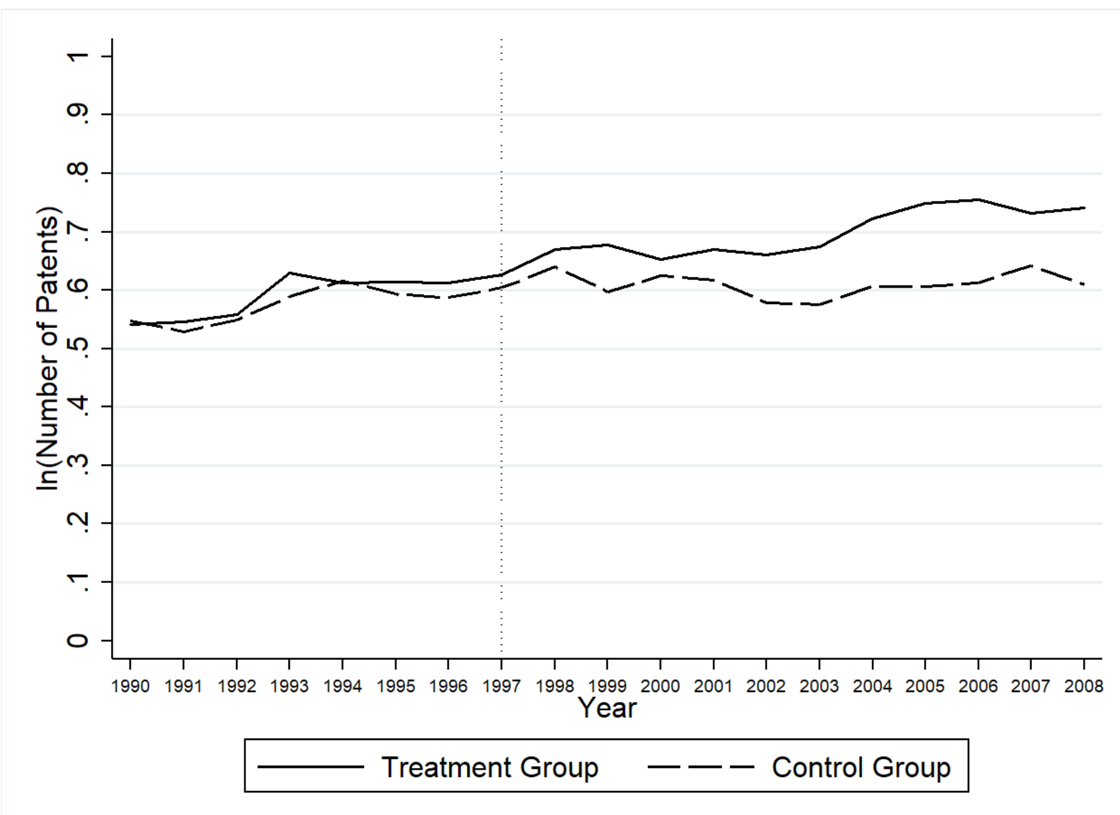
With our new sample, we first test whether the common trends assumption still holds. Figure 5 shows that the common trends assumption still holds because the trends are again parallel before

[38] The other two forms of spillovers—collaboration between UAS and firms, and agglomeration economies—are highly localized and therefore unlikely to cause contamination of our treatment and control groups

1997. Table VII shows the results of the statistical test for a linear yearly trend; Table VIII shows the results of the statistical test for year dummies. We again find no indication that the pre-treatment trends differ between the treatment and control groups.

Finally, Table IX shows the results of the DiD regression of equation (1) with the reduced sample. The coefficient of $Treatment_{jt}$ is slightly higher than that in the baseline model (13.21*** vs. 12.23***). This slight increase of the coefficient of $Treatment_{jt}$ indicates that the newly specified treatment and control groups suffer less from contamination issues than the treatment and control groups of the baseline model. However, because the increase in the coefficient equals only approximately one percentage point, the contamination of the baseline model appears only marginal. Contamination caused by this first form of mobility appears (if any) to downward biasing the effect.

Figure 5 ln(Number of Patents) for treatment and control group, before and after UAS establishment, without municipalities located at outer limit of the catchment area



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Table 9 Parallel trends assumption, sample without municipalities located at outer limit of the catchment area – linear trends

	Dependent Variable ln(Number of Patents)
Year	0.0101***
	(0.0039)
Year x TG_j	0.0026
	(0.0053)
TG_j	0.2876***
	(0.0519)
Constant	0.2606***
	(0.0350)
AR2	0.0198
R2	0.0202
n	8872
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table 10 Parallel trends assumption, s Sample without municipalities located at outer limit of the catchment area – year dummies

		Dependent Variable ln(Number of Patents)
Year		
	1990	Base Group
	1991	-0.0185
		(0.0225)
	1992	0.0026
		(0.0250)
	1993	0.0421
		(0.0290)
	1994	0.0691**
		(0.0323)
	1995	0.0461*
		(0.0271)
	1996	0.0403
		(0.0290)
	1997	0.0569*
		(0.0315)
Year x TG_j		
	1990	Base Group
	1991	0.0232
		(0.0317)
	1992	0.0145
		(0.0347)
	1993	0.0450
		(0.0382)
	1994	0.0011
		(0.0413)
	1995	0.0261
		(0.0378)
	1996	0.0298
		(0.0399)
	1997	0.0275
		(0.0415)
TG_j		0.2757***
		(0.0557)
Constant		0.2662***
		(0.0384)
AR2		0.0188
R2		0.0205
n		8872
p-Value		0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Results of the joint F-test for the interaction between the year dummies and the variable TG equals 0.8429 (Prob. > F)

Table 11 OLS results, sample without municipalities located at outer limit of the catchment area

	Dependent Variable ln(Number of Patents)
Year	yes
TG_j	0.1247
	(0.0893)
$Treatment_{jt}$	0.1321***
	(0.0277)
Constant	0.4350***
	(0.0603)
AR2	0.2531
R2	0.2578
n	17744
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

The second form of mobility that may cause problems is UAS graduates not commuting but instead moving across the regional boundaries that we have defined. To analyze the moving behavior of UAS graduates, we use a representative survey for Switzerland, the Survey of Higher Education Graduates (EHA), which is provided by the Swiss Federal Statistical Office. This survey, conducted biannually since 2002, contains information on where graduates reside during their studies, and five years after graduation. In addition, the EHA provides information on the location of firms in which graduates work five years after their graduation. We use information on graduates from engineering, IT, chemistry, and the life sciences from 2002 to 2008 because their moving behavior is relevant for our study. Using this dataset, we examine two different indicators: First, we look at how many UAS graduates still live in the same UAS catchment area in which they graduated. The results show that five years after graduation, approximately 75 percent of UAS graduates still live in the same UAS catchment area in which they graduated. Thus, moving across the boundaries of our regions is a rather restricted problem.

The third form of mobility that may cause contamination are graduates commuting to another catchment area than they graduated in. To investigate this form of mobility, we examine the firms—and their locations—in which graduates work five years after graduation. As an indicator for the extent of this form of contamination, we take the net fluctuations[39] between the catchment areas for the following reasons: If graduates from a UAS catchment area start working in a control group area, our estimation results would be downwardly biased; conversely, if graduates are evenly distributed across the areas, i.e., if the net fluctuations between the different UAS catchment areas are low, contamination is low and our results would be only marginally affected.[40] The results for the net fluctuations appear in Table 12.

For 80 percent of the UAS catchment areas, the net fluctuations equal at maximum one percentage point, meaning that incoming and outgoing UAS graduates cancel one another out across treated regions. The three exceptions are Winterthur, with a negative net fluctuation of approximately minus three percentage points, i.e., fewer graduates coming in then going out; Bern, with a positive net fluctuation of approximately four percentage points; and Zurich, with a positive net fluctuation of eight percentage points. Thus, even in the region with the largest net fluctuation,

[39] For each catchment area, we calculate the relative share of UAS graduates using the initial survey and the follow-up survey. The difference between these two shares shows the net fluctuation between the catchment areas in percentage points.

[40] The results would imply a downward bias.

the problem remains insignificant because the great majority of the graduates are distributed evenly across the regions.

Although all forms of mobility—commuting or moving—might lead to contamination of the treatment and control groups, these issues cause only very limited problems in our Swiss data. Therefore, studying this policy reform in Switzerland provides an almost ideal setting for analyzing the causal effects of applied research on innovation. However, even if mobility were an empirical concern, the resulting contamination effect would lower the effect sizes and potential significance—and therefore make our test stronger—and the true effect size is likely to be even higher.

Table 12 Net fluctuations across UAS catchment areas

UAS Catchment Area	Net Fluctuations in percentage points
Control Group	-0.0214
Bern	0.0387
St. Gallen	-0.0089
Rapperswil	-0.0123
Burgdorf	-0.0012
Olten	-0.0099
Buchs	-0.0028
Winterthur	-0.0340
Biel	-0.0084
Chur	-0.0042
Wädenswil	0.0025
Burgg-Windisch	0.0029
Zürich	0.0779
Muttenz	-0.0114
Horw	-0.0053
Oensingen	-0.0025

Notes: Authors’ calculations, based on SFSO Survey of Higher Education Graduates

2.6.2 Unobservable Characteristics of Municipalities

In a second robustness check, we focus on the economic background of even smaller regional entities, i.e., municipalities instead of districts. In other words, we include municipality fixed effects in our baseline estimation equation. In doing so, we are able to control for unobservable time-constant characteristics at the lowest possible level. In addition, the inclusion of these control variables reduces the residual variance of our outcome variable and, consequently, increases the precision of our point estimates (Angrist & Pischke, 2008). We are therefore able to investigate the common trends assumption even more carefully, as the municipality fixed effects increase the likelihood of detecting different pretreatment trends between the treated and the untreated regions.

Equation 2 is identical to Equation 1 in the baseline model but contains dummies for municipalities, π_j. The only difference is that the municipality fixed effects are perfectly collinear with the treatment dummy TG_j and therefore cancel it out. Thus we estimate:

Equation 2 $$ln(Number\ of\ patents_{jt+3}) = \alpha + \beta Treatment_{jt} + \gamma_t + \pi_j + \varepsilon_{jt}$$

Table 13 shows the results of the common trends analysis in the linear specification, Table 14 in the nonlinear specification. The coefficient of the interaction *Year x* TG_j reveals whether the treatment and the control group have different trends before the establishment of UAS. In both specifications, the interaction is not statistically significant. Thus, even including municipality fixed effects and therefore increasing the precision of the point estimates, we find no indication for a violation of the common trends assumption.

Table 13 Parallel trends assumption, municipality fixed effects – linear trend

	Dependent Variable ln(Number of Patents)
Year	0.0101***
	(0.0030)
Year x TG_j	0.0035
	(0.0038)
TG_j	excluded
Municipality Fixed Effects	yes
Constant	0.4348***
	(0.0079)
AR2	0.8027
R2	0.8274
n	11480
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table 14 Parallel trends assumption, municipality fixed effects – year dummies

	Dependent Variable ln(Number of Patents)
Year	
1990	Base Group
1991	-0.0185
	(0.0277)
1992	0.0026
	(0.0272)
1993	0.0421
	(0.0286)
1994	0.0691**
	(0.0289)
1995	0.0461*
	(0.0268)
1996	0.0403
	(0.0274)
1997	0.0569*
	(0.0294)
Year x TG_j	
1990	Base Group
1991	0.0092
	(0.0353)
1992	0.0060
	(0.0342)
1993	0.0319
	(0.0353)
1994	0.0039
	(0.0355)
1995	0.0287
	(0.0340)
1996	0.0189
	(0.0347)
1997	0.0289
	(0.0367)
TG_j	excluded
Municipality Fixed Effects	yes
Constant	0.4376***
	(0.0127)
AR2	0.8029
R2	0.8277
n	11480
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Result of the joint F-test for the interaction between the year dummies and the variable *TG* equals 0.9368 (Prob.>F).

Table 15 displays the results of Equation 2. As the coefficient β shows a lower effect than the baseline model, the municipality fixed effects erode part of the innovation effect. Given that they control for unobservable time-constant characteristics at a much lower level than the district fixed effects, this decrease in the innovation effect is in line with our expectations.[41] However, the effect still equals 7.7 percent and is statistically significant at the one percent level.

This specification including municipality fixed effects thus demonstrates that the common trends assumption is not violated even increasing the precision of the estimates. In addition, the specification shows that the effect, though smaller, remains robust to the inclusion of municipality fixed effects and is not induced by the municipalities' underlying unobservable time-constant characteristics.

Table 15 OLS results for patent quantity, municipality fixed effects

	Dependent Variable ln(Number of Patents)
Year	yes
TG_j	excluded
$Treatment_{jt}$	0.0739*** (0.0115)
Municipality Fixed Effects	yes
Constant	0.5028*** (0.0153)
AR2	0.8015
R2	0.8140
n	22960
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

[41] Switzerland consists of approximately 2,300 municipalities and 148 districts (retrieved January 2019 from https://www.bfs.admin.ch/bfs/de/home/statistiken/querschnittsthemen/raeumliche-analysen/raeumliche-gliederungen.html).

2.6.3 Development of the Innovation Effect over Time

In a further robustness check, we examine timing issues. As the baseline model shows only the average effect of the establishment of UAS on innovation over the entire observation period, we now investigate how the effect develops over years, i.e., in the first, second, third, and further years after the UAS were established. To do so, we estimate the following equation:

Equation 3 $$ln(Number\ of\ patents_{jt}) = \alpha + \sum_{t=-m}^{q} \beta_t Treatment_{jt} + \pi_j + \gamma_t + \varepsilon_{jt}$$

The variable *ln(Number of patents$_{jt}$)* refers to the natural logarithm of the number of patents in municipality *j* in year *t.* Because we are interested in the effect of the UAS establishment in each post-treatment year, we do not include the time lag (t+3) that we included in the baseline estimation.[42] The estimation results of this specification thus shows the size of the invention effect in each year following the establishment of UAS campuses. The results therefore verify the adequacy of the three-year time lag. Finally, as in Equation 2, we include municipality fixed effects to control for unobserved time-constant municipality characteristics.

Our variable of interest is *Treatment$_{jt}$*. While the variable was binary in the baseline model and the preceding robustness tests, we now create dummy variables indicating the pre-treatment years (*t-11, t-10,…, t-1*), the year of UAS establishment (*t=0*), and the post-treatment years (*t+1, t+2,…, t+11*). Thus we again exploit the staggered establishment of the different UAS campuses and pool the data for the year in which each UAS campus was created.

Table 16 shows the results of Equation 3. In the first column, we include all municipalities; in the second, we exclude those municipalities whose UAS campus closed down.[43] The coefficients for dummies *t -11* to *t-1* show the effects of UAS establishment for the pre-treatment years relative to the year of UAS creation, *t=0*. A positive effect in this period, particularly in the years close to *t=0*, would indicate that the assignment of the treatment was endogenous (see, e.g., Angrist & Pischke, 2008). In other words, an increase in patenting activities before the reform would indicate

[42] Because Equation 3 does not include a time lag for the dependent variable *ln(number of patents$_{jt}$)*, the number of observations—the n in Table 16—increases because the time lag makes us lose three years of observations.

[43] The first column in Table 16 includes campuses that shut down due to relocation (e.g., Bern and Oensingen in 2003). For these catchment areas, the year dummies indicating the post-treatment period underestimate the innovation effect because they measure the effect of a UAS that no longer exists in that region.

that the location and timing of the establishment of UAS campuses were related to innovative, technical or economic factors. However, as expected, there are hardly any effects for these years in the pretreatment period.[44]

In the post-treatment years, the effects are strong. Only the coefficients for the first two years after the establishment of UAS are small—approximately 1.4 and 3.5 percent—and insignificant. In the following years, the effect equals 4 percent in $t+3$ and increases to more than 13 percent in later years. Thus the results clearly show that, first, the innovation effect takes time to manifest after the establishment of UAS; a time lag of three years therefore seems adequate to estimate the effect of the UAS on innovation in our baseline model. Second, the results show that the innovation effect increases over time.

[44] Given that some dummies show a statistically significant and negative effect in the years before the establishment of UAS, results might be underestimated. Nonetheless, given no further systematic pattern over the subsequent years, we conclude that the regions show sufficiently similar trends before the treatment.

Table 16 OLS results for patent quantity, effects for pre- and post-treatment years

	Dependent Variable ln(Number of Patents)	
	(1) Sample with campuses that underwent relocation	(2) Sample without campuses that underwent relocation
Year	yes	yes
$Treatment_{jt}$		
t minus 11	-0.0435	-0.0444
	(0.1363)	(0.1368)
t minus 10	-0.1249*	-0.1219*
	(0.0668)	(0.0676)
t minus 9	-0.1391**	-0.1220*
	(0.0692)	(0.0701)
t minus 8	-0.0017	0.0068
	(0.0391)	(0.0439)
t minus 7	-0.0416	-0.0486
	(0.0305)	(0.0335)
t minus 6	-0.0654**	-0.0586*
	(0.0290)	(0.0317)
t minus 5	-0.0674**	-0.0634**
	(0.0288)	(0.0318)
t minus 4	-0.0504*	-0.0521*
	(0.0277)	(0.0305)
t minus 3	-0.0299	-0.0294
	(0.0270)	(0.0295)
t minus 2	0.0083	0.0191
	(0.0277)	(0.0304)
t minus 1	0.0059	0.0045
	(0.0252)	(0.0279)
t 0	Base Group	Base Group
t plus 1	0.0293	0.0351
	(0.0241)	(0.0268)
t plus 2	0.0143	0.0233
	(0.0256)	(0.0283)
t plus 3	0.0379	0.0390
	(0.0260)	(0.0282)
t plus 4	0.0478*	0.0479
	(0.0269)	(0.0295)
t plus 5	0.0611**	0.0646**
	(0.0275)	(0.0303)
t plus 6	0.1051***	0.1190***
	(0.0284)	(0.0313)
t plus 7	0.1150***	0.1255***
	(0.0294)	(0.0324)
t plus 8	0.0983***	0.1006***
	(0.0296)	(0.0324)
t plus 9	0.0865***	0.0953***
	(0.0311)	(0.0344)
t plus 10	0.0711**	0.0834**
	(0.0324)	(0.0359)
t plus 11	0.0431	0.0561
	(0.0371)	(0.0398)
Constant	0.4649***	0.4953***
	(0.0239)	(0.0255)
AR2	0.7825	0.7844

R2	0.7942	0.7961
n	27265	23902
p-Value	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Robust standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Column (1) shows the results including all UAS campuses; column (2) shows the results without campuses that underwent relocation. Regressions in column (1) and (2) include year dummies for the common time trend and municipality fixed effects.

2.6.4 Confounding Effects: Education Expansion of Academic Universities

The next robustness check relates to the question of whether an educational expansion of conventional academic universities could also potentially drive our results. Although the number of these conventional academic universities has remained unchanged for the last 100 years in the German-speaking area of Switzerland, the number of students has increased substantially.[45] In 1990, for example, 86,000 students were enrolled in an academic university; by 2008, the number had increased to 120,000.[46] This expansion of academic graduates constitutes a change in the labor supply that may also substantially affect innovation in our regions.

To compare the importance of the two different supply changes of highly skilled workers—the increase in UAS graduates due to the establishment of UAS, and the increase in academic university graduates—we use data from the "Schweizer Hochschulinformationssystem" (SHIS) provided by the Swiss Federal Statistical Office. This data source includes all university and UAS graduates from 2000 to 2008 who studied engineering, IT, chemistry, or the life sciences. In addition, SHIS has information about the graduates' place of residence[47] and their year of graduation, allowing us to construct the cumulative number of graduates in each municipality over the years and, therefore, the intensity of the two shocks.[48]

The difference-in-differences method allows us to estimate how changes in this intensity affect regional innovation. In other words, our empirical framework measures the effect of the labor supply changes of UAS and of academic graduates. The variable $University\ Graduates_{jt}$ includes the cumulative number of conventional academic university graduates in year t in municipality j and thus reflects the intensity of the labor supply change induced by the educational expansion of academic university graduates. Similarly, the variable $UAS\ Graduates_{jt}$ comprises the cumulative

[45] In the German-speaking part of Switzerland, which is the area that is relevant for our study, only one academic university was created (in 2000). However, this university, which is located in Lucerne, does not offer studies in engineering, IT, chemistry, or the life sciences (see https://www.unilu.ch/).

[46] See SFSO, SHIS, at https://www.bfs.admin.ch/bfs/de/home/statistiken/bildung-wissenschaft/personen-ausbildung/tertiaerstufe-hochschulen.html (retrieved January 2019).

[47] SHIS provides information about the place of residence when students receive their admission requirements for a university. We therefore have to assume stable moving behavior. As shown in 2.6.1 Contamination of Treatment and Control Groups, 75 percent of UAS graduates remain living in the catchment area five years after graduation. The ratio for university graduates having graduated in comparable subject areas equals 70 percent. Assuming stable moving behavior is therefore plausible.

[48] See, e.g., Meyer (1995), and Card (1992) who refer to the intensity of a policy reform in a difference-in-differences setting.

number of UAS graduates in year *t* in municipality *j* and represents the change of skilled workers resulting from the establishment of UAS. To measure the effect of the change in the labor supply, we include these two variables in our baseline model and estimate Equation 4:

Equation 4

$$ln(Number\ of\ patents_{jt+3}) = \alpha + \beta Treatment_{jt} + \theta_U University\ Gradates_{jt+3} + \theta_{UAS} UAS\ Graduates_{jt+3} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

Column (6) of Table 17 reports the results where both variables for the UAS graduates and those of academic universities are included in the estimations to see how they compare to each other. Whereas the effect for university graduates is statistically insignificant, the effect for UAS graduates remains very strong at more than 3 percent and is statistically significant at the 1 percent level. The comparison of the two supply changes therefore shows that the effect on regional patenting activity is induced not by the increase in university graduates but largely by the increase in UAS graduates and, consequently, by the establishment of UAS.

Including the binary variable $Treatment_{jt}$ in column (7) changes neither the size nor the significance of the two coefficients. However, the coefficient of the variable $Treatment_{jt}$ decreases substantially, compared to the same coefficient in the baseline specification. The supply change of the UAS graduates thus captures a considerable portion of the innovation effect. This portion of the innovation effect is therefore attributable to direct spillovers of UAS: graduates entering the labor market, remaining in it, and enhancing its quality. The remaining innovation effect relates to the other forms of spillovers—collaboration between UAS and firms, and agglomeration economies—or merely UAS professors producing patents.

Table 17 OLS results for patent quantity, comparison academic university expansion with UAS creation

	Dependent Variable ln(Number of Patents)						
	Baseline Model	UAS Graduates		University Graduates		UAS and University Graduates	
Year	yes	yes	yes	yes	yes	yes	yes
TG_j	0.0718	0.1155*	0.0847	0.1159*	0.0842	0.1152*	0.0849
	(0.0706)	(0.0661)	(0.0676)	(0.0670)	(0.0682)	(0.0662)	(0.0676)
$Treatment_{jt}$	0.1223***		0.0654**		0.0671**		0.0642**
	(0.0266)		(0.0288)		(0.0303)		(0.0302)
UAS $Graduates_{jt}$		0.0380***	0.0378***			0.0330***	0.0330***
		(0.0108)	(0.0108)			(0.0079)	(0.0079)
University $Graduates_{jt}$				0.0351***	0.0349***	0.0055	0.0054
				(0.0129)	(0.0129)	(0.0154)	(0.0154)
Constant	0.4507***	0.4189***	0.4413***	0.4186***	0.4416***	0.4191***	0.4411***
	(0.0546)	(0.0513)	(0.0527)	(0.0520)	(0.0532)	(0.0514)	(0.0527)
AR2	0.2513	0.3080	0.3082	0.3001	0.3003	0.3082	0.3084
R2	0.2551	0.3115	0.3117	0.3036	0.3038	0.3117	0.3119
n	22960	22960	22960	22960	22960	22960	22960
p-Value	0.0000	0.0001	0.0000	0.0002	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

2.7 Conclusion

Our study investigates whether UAS, which were explicitly created and funded to conduct and teach applied research, fosters regional innovation activities. To study their effect on innovation, we exploit an educational policy intervention in Switzerland in the mid-1990s, the establishment of these UAS in the mid-1990s, using a difference-in-differences approach and relying on patent data provided by the European Patent Office to measure innovation. As a quantitative measure of innovation activities, we use the number of patent applications. Our results show that the establishment of UAS led to an increase of approximately 7.7 to 13 percent in regional patenting activity.

We provide extensive analyses of the key assumptions of the model, and our results strongly suggest that the increase in innovation quantity is indeed a causal effect of the establishment of UAS. First, we find no evidence for a violation of the first key assumption of the difference-in-differences model, the common trends assumption. Second, we find that the contamination of the treatment and control groups—the second key assumption of our model—affects our results only marginally, if at all, because there is almost no net fluctuation in UAS graduates across our regions and because when we exclude a belt of municipalities at the outer border of our treated regions, the results only become stronger. Moreover, even if contamination were a problem, the true effect would be even higher because UAS graduates would raise patents in the control group instead of the treatment group, and our results would then underestimate the size of the effect. Thus we are confident that our results indeed measure a causal effect of the establishment of UAS on regional innovation activities, and, if at all, underestimate the effect.

The results of our further robustness tests show that differences between the regions (municipality fixed effects) do not change our results and that the effect is not driven by an overall educational expansion. Thus we conclude that it is the applied research aspect of UAS—which by legal mandate is the constituting difference between the UAS and the academic universities (and their respective graduates)—that is the essential driver of the increased innovation in the regions where they were established.

The results of our robustness tests also provide insights into the potential mechanisms behind this innovation effect. By modelling the innovation effect in each year following UAS establishment, we find that the effect develops over time. The first two years show hardly any effect, but from year three onward, the effect becomes increasingly larger. This time pattern is in line with our theoretical expectations of direct spillovers: First, UAS graduates entering the labor market are bringing new knowledge to the firms and helping them boost innovation. Thus the effect should take hold three years after the establishment of a UAS because that is when the first graduates enter the labor market, following which will be a steady stream of new graduates. Second, the establishment of UAS may affect patenting because of direct research cooperation between professors or students of the UAS with public or private firms in the respective region. Because establishing, funding, and carrying out R&D cooperation projects takes time (often at least three years because of application and funding processes), this second form of direct spillovers would also be consistent with an innovation effect taking hold after three years.

Furthermore, the results of our robustness tests provide some evidence for the relative importance of different mechanisms. They show that a considerable portion of the effect is related to UAS graduates entering the labor market. The remaining innovation effect might be attributed to cooperation between UAS and firms, collaboration between UAS and other research institutes, or UAS professors producing patents. Because no data is readily available for testing these mechanisms, future research should investigate the relative importance of these two forms of direct spillovers.

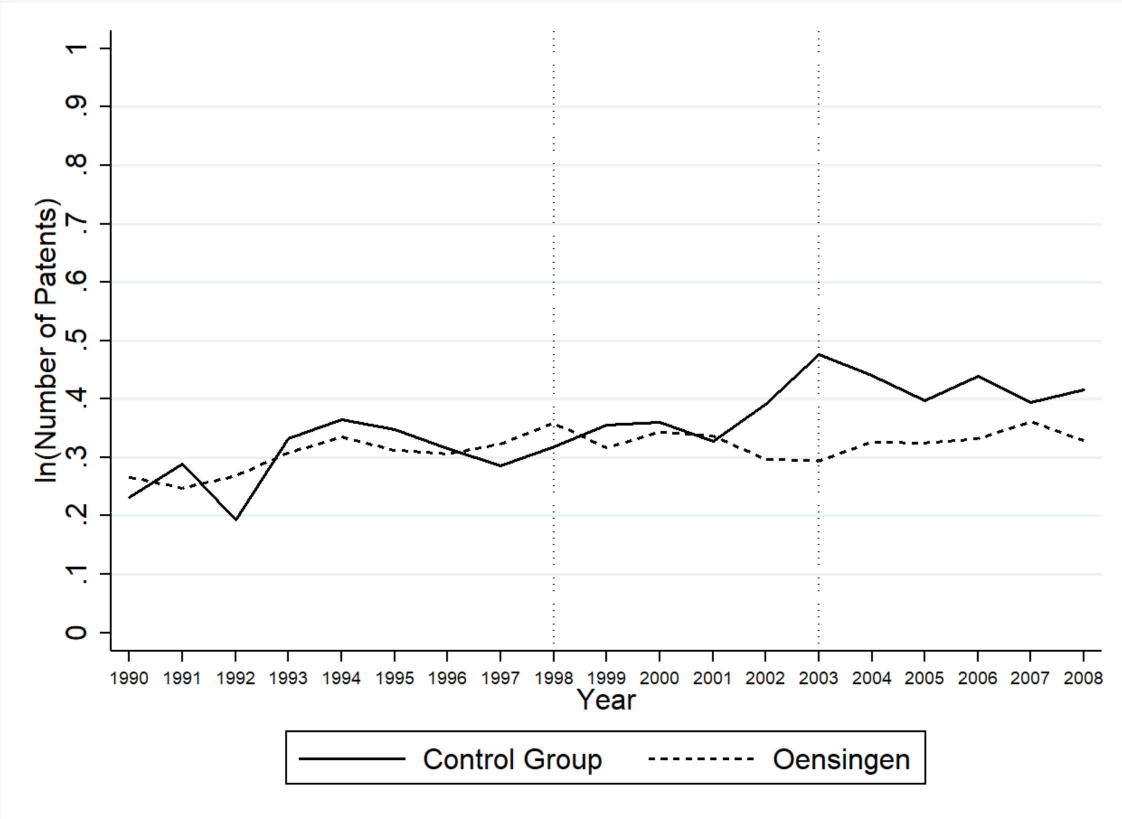
Our analyses thus show strong support that the establishment of UAS, whose constituting characteristic is conducting and teaching applied research, has a causal effect on innovation activities in the regions where they have been established, even when these regions are outside major centers of commercial innovation. UAS therefore constitute an efficient means of fostering and more evenly distributing innovation activities across a country and effectively combining applied research skills with sound vocational knowledge.

2.8 Appendix

The summary of the establishment process of the five UAS demonstrates that political factors are a fundamental determinant of the temporal and spatial variation of the campuses' establishment. In addition, the concentration requirements of the UAS commission and the resulting relocation of campuses allows us to investigate how sensitive a catchment area reacts on campuses that open and close their doors. In the following, we focus on the UAS of Northwestern Switzerland and demonstrate how patenting activities in the catchment areas of the campus of Oensingen (opening in 1998 and closing in 2003) and Olten (opening in 2003 and closing in 2006) change. Figure A1 shows the natural logarithm of the number of patent applications for the treatment group, i.e., all municipalities located in the catchment area of the campus in Oensingen, and of the number of patent applications for the control group. Before the establishment of the campus in 1998, the treatment and the control groups exhibited parallel trends. After 1998, patenting activity in the treated municipalities increased after a three-year time lag. After the relocation of the campus in Oensingen to Olten in 2003, patenting activities again decreased.[49]

[49] We do not find statistically significant differences in the trends between the treatment and the control group. Estimating our baseline equation for this subsample (including the municipalities of the control group and those of the catchment area of the campus in Oensingen), we find a 12 percent increase in patenting activities. The effect is statistically significant at the ten percent level.

Figure A1 ln(Number of Patents) for treatment and control group, catchment area of Oensingen (establishment in 1998, relocation in 2003)

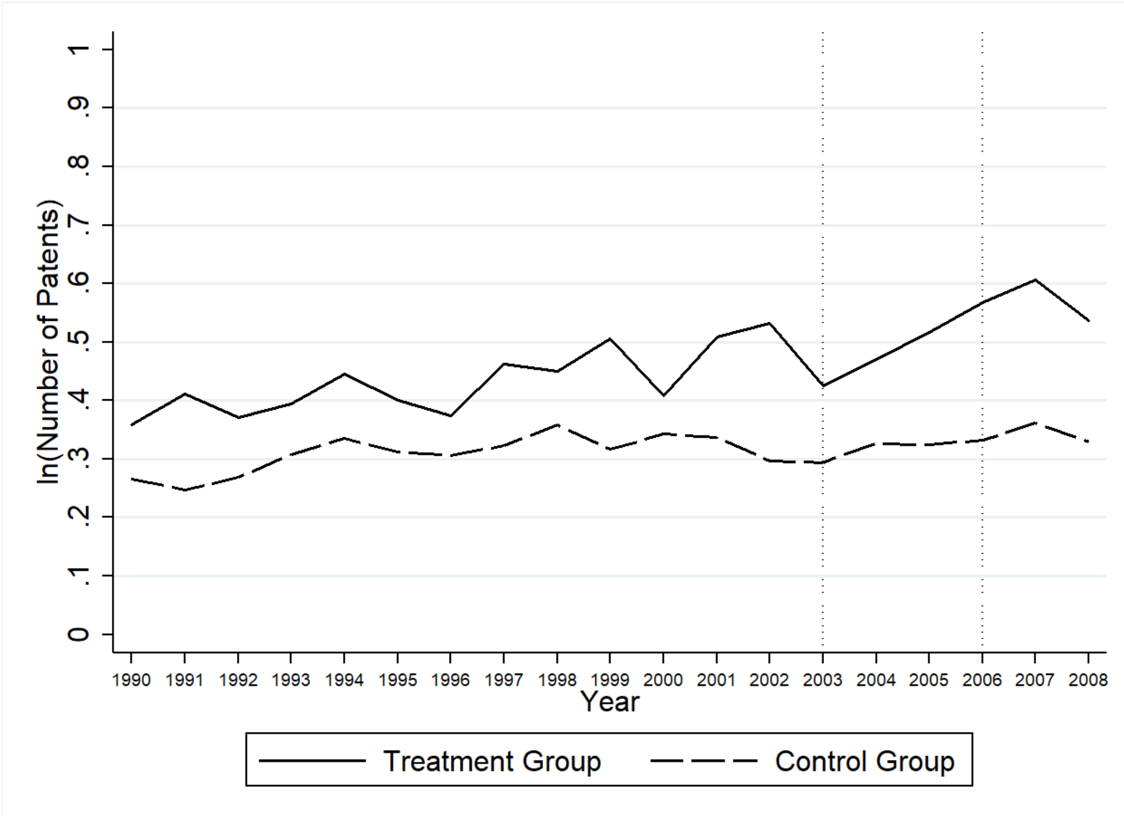


Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version.

Figure A2 shows the same graph for the catchment area of the campus in Olten. After the relocation of the campus in Oensingen to Olten, patenting activity increased in the catchment area of Olten; when engineering and IT moves to Brugg-Windisch in 2006, patenting activities decrease.[50] The establishment and relocation of the campuses in Oensingen and in Olten thus show that municipalities can react very sensitively to campuses opening and closing their doors.

[50] We do not find different pre-treatment trends between the treatment and the control group. The effect of the campus in Olten on patenting activities equals 25 percent. The effect is statistically significant at the one percent level.

Figure A2 ln(Number of Patents) for treatment and control group, catchment area of Olten (establishment in 2003, relocation in 2006)



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version.

Chapter 3

Tertiary Vocational Education and Innovation – Quality

Part of this chapter is an extended version of early parts of the working paper "Regional Effects of Applied Research – Universities of Applied Sciences and Innovation", by Pfister, Rinawi, Harhoff & Backes-Gellner, 2016.

3.1 Introduction

The results of the preceding chapter show that the number of patent applications increased by 13 percent in regions where a UAS was established. UAS have thus a positive effect on regional patenting in terms of quantity because patents are a proxy of new technology creation (see, e.g., Acs, Anselin, & Varga, 2002; Hall, Jaffe, & Trajtenberg, 2001). However, not all patents are equally important, whereas some are more valuable, others are less (van Zeerbroeck, 2011). The economic value of patents thus greatly differs (Acs et al., 2002; Griliches, 1979, 2007). Moreover, previous literature shows that the majority of patents have little or no value and that few patents have a very high value; in other words, the value distribution of patents is highly skewed, with a very long right tail (see, e.g., Gambardella, Harhoff, & Verspagen, 2008; van Zeebroeck, 2011). The number of patents (and patent applications) is therefore not a good measure for patent quality (Harhoff, Scherer & Vopel, 2003). Estimating the effect of the establishment of UAS on patent quality therefore requires further measures that take into account the value distribution of patents.

In this chapter, we focus on the quality aspects of patents. In a first step, we provide a definition of the concept of patent value and an overview of (some) possible measures that allow capturing this value. In a second step, we describe the measures we use in our analysis—grant status, forward citations, claims, and patent family size—and present descriptive statistics relying on our patent data base, the Worldwide Patent Statistical Database – April 2013 Version. We then explain our empirical framework—the difference-in-differences method—and present our estimation results, showing an increase in all quality measures due to the establishment of UAS. This chapter thus demonstrates that the establishment of UAS increased both the quantity and the quality of innovation. UAS, therefore, consist of an important alternative to academic universities to increase not only the quantity but also the quality of regional innovation activities.

3.2 Patent Quality

Squicciarini, Dernis, and Criscuolo (2013) define *patent quality* as "the technological and economic value of patented inventions" (p. 7). Their broad definition considers that the literature does not provide a concise definition of patent quality because patent quality encompasses different aspects of value (OECD, 2009; Hall & Harhoff, 2012; Harhoff et al., 2003). These different aspects of value include the *social* and the *private value* of a patent. The *social value* refers to the determination of how much an invention contributes to the stock of technology of the society. The *private value* shows how valuable the patent is for the patent holder, e.g., in terms of the discounted flows of profits for the patent holder (OECD, 2009; Gambardella et al., 2008). This private value is further differentiable, comprising the *invention value* and the *patent premium* (see, e.g., OECD, 2009; Gabmardella et al., 2008; Arora, Ceccagnoli & Wesley, 2008). The *invention value* is the patent's contribution to the state of the art, i.e., the quality or the content of the invention (OECD, 2009). The *patent premium*—the value of the patent itself—refers to the value the invention creates for the holder in addition to the invention value, "the difference between the value of the invention as it is patented and the value it would have had if it had not been patented" (OECD, 2009: 136).[51] Similar to the number of value concepts, the literature provides various methods[52] and indicators to measure them.

[51] For further details about the different aspects of the private and the social value of a patent, as well as the different approaches to measure them, see for example Gambardella et al. (2008), Hall and Harhoff (2012), OECD (2009), Harhoff et al. (2003).

[52] To infer the patents' private economic value, researchers in previous literature a) asked patent holders or inventors about the economic value of their patents conducting surveys, b) used data from the patenting procedure, i.e., the strategy that we follow, and c) related financial data of companies to their patenting activity (OECD, 2009).

The resulting patent value distributions differ among the different evaluation techniques because they relate to different value aspects (for further details, see e.g. Gambardella et al., 2008; Hall & Harhoff, 2012): The first technique, for example, considers patents as an asset and therefore determines a patent value including both, the invention value and the patent premium. This technique thus includes the strategic role of patent rights, for example, that selling of a patent might block the revenues of complementary or cumulative inventions. Inferring the value of patents using renewal fees—an evaluation technique that uses indirect value measures from the patenting procedure—ignores this strategic role of patents. By using a set of value indicators from the patenting procedure and applying difference-in-differences estimations, we address this problem. Our results therefore show the change in a set of different value aspects for the treatment group relative to the control group.

Another issue we have to keep in mind using data from the patenting procedure is that the indicators are indirect measures and therefore proxies for patent quality (Squicciarini et al., 2013). Their relation to the skewed value distribution of patents is therefore noisy (see, e.g., Harhoff, Narin, Scherer, & Vopel, 1999; Gambardella et al., 2008).

3.3 Measures for Patent Quality

Squicciarini et al. (2013) present an overview of different quality measures that mirror different aspects of value: Some of the measures relate rather to the social value, and others relate rather to the private value; some have a stronger technological connotation, while others have a stronger economic connotation (Squicciarini et al., 2013). To estimate the effect of the establishment of UAS on these different value aspects, we, therefore, use a set of quality indicators. This set includes the following indicators: granted patents, forward citations, number of claims, and patent family size:

Granted patents constitute a first quality indicator because a granted patent fulfills the patentability criteria (inventive step, novelty, and industrial applicability) and is therefore technologically and economically more valuable than an unsuccessful patent application. However, as a large share of applications are granted, the indicator is less informative (OECD, 2009; van Zeebroeck, 2008).

Forward Citations refer to the number of citations a patent receives by subsequent, new patents (in our study, within three and five years after application). Forward citations thus show the relation and the differences to subsequent inventions and indicate the state of the art upon which new inventions are built. On the one hand, forward citations therefore mirror the importance of the patented technology, i.e., the private economic value, for the patent holder: The more a patent is cited, the more valuable it is for the owner. On the other hand, forward citations capture the economic externality of the invention, i.e., its social value, for those not holding the patent: The more a patent is cited, the more important it is in contributing to new inventions. (see, e.g., Harhoff et al., 1999; Griliches, 1990; OECD, 2009; Squicciarini et al., 2013; Gambardella et al., 2008; Lanjouw & Schankerman, 2004; van Zeebroeck, 2011). Previous literature provides empirical evidence that forward citations mirror both private economic value (see, e.g., Hall et al. 2005; Harhoff et al. 1999) and social value (Trajtenberg, 1990). However, although a large number of forward citations correlate with a high private economic patent value, the relationship is noisy (Harhoff et al., 1999).

The *number of claims* in a patent specification defines the boundaries of the property rights that the patent protects (see, e.g., Lanjouw & Schankerman, 2004; Squicciarini et al., 2013). The broader the scope of the patent, i.e., the more claims it involves, the broader the technological area that is legally protected and the higher the economic value of the patent (OECD, 2009).[53] Empirical evidence shows the importance of claims as a qualitative indicator (see Lanjouw & Schankerman, 2004).

Patent family size refers to the number of countries in which the same invention is protected (Lanjouw & Schankerman, 2004; van Zeebroeck, 2011; Harhoff et al., 2003; Putnam, 1996; OECD, 2009). Only patents of higher expected value have protection in several countries, as filing and enforcing the invention in different jurisdictions is costly (van Zeebroeck, 2011; Squicciarini et al., 2013). Empirical evidence shows a positive correlation between the number of jurisdictions and patent value (Harhoff et al, 2003; Lanjouw & Shankerman 2001; Schmoch, Grupp, Mannsbart & Schwitalla, 1988). Patents of particular high value are triadic patent families, applications filed in the three largest patent offices, i.e., in the USPTO, in the EPO, and in the Japanese Patent Office (Guellec & van Pottelsberghe de la Potterie, 2005; Harhoff et al., 2003; Sapsalis & van Pottelsberghe de la Potterie, 2007; van Zeebroeck, 2011).

This brief description shows the importance—or even the inalienability—of using a set of quality measures instead of a single measure. Previous literature provides empirical evidence that these measures relate to the value of patents (see, e.g., Gabmardella et al. 2008; Harhoff et al. 1999; Harhoff et al. 2003). However, to what extent they measure different aspects of value—such as the invention value, the patent premium, the asset value for the patent holder, or the value of the invention for the society—is unclear and still debated among experts (OECD, 2009; van Zeebroeck, 2011).

On the one hand, the literature shows that they constitute an important indicator of some common underlying notion of patent quality: Lanjouw & Schankerman (2004) create a quality index that includes the indicators, namely, forward citations, backward citations[54], claims and family size and that captures a common notion of technological and economic quality of the patents. Similarly, van Zeebroeck (2011) performs a factor analysis with a set of indicators (e.g.,

[53] However, the tendency to overstate the number of claims implies that the measure is quite noisy (OECD, 2009).

[54] *Backward citations* refer to a patent's references to preceding patents, mirroring a potentially valuable technological area (Lanjouw & Schankerman, 2004; OECD, 2009; Squicciarini et al, 2013). However, a large number of backward citations might also indicate that the patented invention is rather incremental (Lanjouw & Schankerman, 2004).Whereas Lanjouw & Schankerman (1997) find no statistically significant relation between this indicator and patent value, Harhoff et al. (2003) find that backward citations are positively related with patent value.

grant status, forward citations, renewals[55], patent family size, etc.) and finds three underlying factors. The first factor relates to the grant status of an application; the second might relate to the value remaining once the value effect by the grant decision is removed and includes the variables forward citations, renewals, and patent family size; the third factor relates to opposition[56], an indicator that is orthogonal to the others. Most indicators are thus interrelated and capture a common notion of technological and economic value.

On the other hand, besides this common notion of quality, the indicators capture differing quality aspects. Van Zeebroeck (2011) shows that the indicators in his factor analysis maintain a high degree of uniqueness, suggesting that many unexplained aspects remain in the relation between patent value and their proxies. In other words, patent value rankings that rely on different indicators differ substantially among these indicators because they capture—besides a common notion of quality—differing quality dimensions, industrial patterns, or opposite evolutions (van Zeebroeck, 2011). Further empirical evidence showing a strong correlation between indicators and patent value but a weak correlation between the different indicators corroborate these findings and stress the importance of using various quality measures (see, e.g., Gambardella et al., 2008; Harhoff et al. 2003; Lanjouw & Schankerman, 2004; van Zeebroeck, 2011).

Thus, to analyze the effect of the establishment of UAS on changes of both a common underlying notion of patent quality and different aspects of patent quality that mirror different dimensions of private and social patent value, we use a set of quality indicators including granted patents, forward citations, number of claims, and patent family size.

[55] *Patent renewals* refer to the fees a patent holder has to pay to keep the patent maintained in the different jurisdictions. As keeping a patent alive is costly, patent renewals reflect the economic value of an invention (Harhoff et al., 2003; OECD, 2009; Squicciarini et al., 2013; van Zeebroeck, 2011). However, this indicator is related rather to a lower bound of the patent's economic private value, as it measures the patent premium (Gambardella et al., 2008).

[56] *Opposition* is an indicator that exploits a third party's possibility to oppose granted patents; these patents whose validity is challenged are considered to have a higher economic value because legal battles are costly (Gambardella et al, 2008; Harhoff et al., 2003; van Zeebroeck, 2011; OECD, 2009). In addition, the different outcomes following an opposition case—maintenance, amendment, or revocation of a patent—inform about the value of a patent: Harhoff et al. (2003) show that patents surviving opposition are of particularly high value.

3.4 Data

To analyze the effect of the UAS establishment on the quality of inventions, we use the "Worldwide Patent Statistical Database – April 2013 Version" provided by the European Patent Office.[57] This database contains a binary variable indicating whether a patent application was granted; this variable consists of our qualitative indicator *granted patents*.

The indicator *forward citations* includes the number of citations for each patent application. Following previous literature, we use a five-year citation lag between the application date of the cited patent and the application date of the citing patent.[58] We additionally use a citation lag of three years, following the argumentation by Lanjouw & Schankerman (2004). The authors argue that patent applications having forward citations with a short citation lag are technologically valuable because they indicate rapid recognition of the technology and other individuals conducting research in the technological area. Thus, an increase in the number of forward citations that appear three years after patent application—compared to five years after application—indicates higher expected value and importance of the invented technology.

To create the indicator *number of claims*, our measure for the scope of a patent, we use the number of claims of each patent application in the latest EP and in the latest US publication. Finally, the indicator *patent family size* refers to a variable that shows the number of jurisdictions in which the same invention is protected. Table 18 and Table 19 show summary statistics for these indicators for the treatment and the control groups before and after the establishment of UAS.

[57] We link the indicators using the application identifier number *appln_id*

[58] One problem regarding the indicator forward citations is its timeliness: As the citations that a patent receives appear over time, the indicator is censored to the right. Limiting the citation lag to a specific number of years solves the problem of timeliness (OECD, 2009). Previous literature usually uses a lag of five years, as more than 50% of citations arise within this number of years (Gabmardella et al., 2008; Lanjouw & Schankerman, 2004; OECD, 2009; van Zeebroeck, 2011). Lanjouw & Schankerman (1998) argue that a five-year citation lag is sufficiently meaningful for a forward citation indicator.

Table 18 Descriptive statistics for quality indicators

		Untreated regions				Treated regions			
	Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Before the UAS establishment	Number of Granted Patents	0.75	6.14	0.00	166.00	1.38	6.78	0.00	167.00
	Number of Citations per Patent (3 year citation lag)	0.08	0.37	0.00	7.00	0.14	0.47	0.00	12.00
	Number of Citations per Patent (5 year citation lag)	0.15	0.59	0.00	7.00	0.28	0.89	0.00	17.00
	Number of Claims US	1.65	4.91	0.00	83.00	2.82	5.75	0.00	67.78
	Number of Claims Europe	1.33	3.82	0.00	39.00	2.36	4.89	0.00	83.85
	Family Size	0.67	2.06	0.00	25.64	1.22	2.64	0.00	28.00
After the UAS establishment	Number of Granted Patents	1.00	10.12	0.00	277.00	2.43	13.33	0.00	407.00
	Number of Citations per Patent (3 year citation lag)	0.11	0.73	0.00	30.00	0.21	0.61	0.00	10.79
	Number of Citations per Patent (5 year citation lag)	0.21	0.97	0.00	31.00	0.41	1.09	0.00	19.81
	Number of Claims US	1.86	5.60	0.00	171.00	3.51	6.74	0.00	83.00
	Number of Claims Europe	1.57	4.52	0.00	79.98	3.02	5.82	0.00	64.00
	Family Size	0.70	2.17	0.00	41.69	1.43	3.03	0.00	32.35
	Number of Municipalities	392				1043			

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version.

Table 19 Descriptive statistics for quality indicators – trends

		Untreated regions		Treated regions	
	Variable	Average trend (in percent)	Std. Err.	Average trend (in percent)	Std. Err.
Before the UAS establishment	ln(Number of Granted Patents per Municipality	0.0090***	(0.0027)	0.0124***	(0.0024)
	ln(Number of Citations per Patent, 3 year citation lag)	0.0044***	(0.0015)	0.0053***	(0.0011)
	ln(Number of Citations per Patent, 5 year citation lag)	0.0071***	(0.0021)	0.0099***	(0.0015)
	ln(Number of Claims US)	0.0128**	(0.0057)	0.0145***	(0.0041)
	ln(Number of Claims Europe)	0.0113**	(0.0054)	0.0140***	(0.0038)
	ln(Family Size)	0.0054	(0.0037)	0.0080***	(0.0028)
After the UAS establishment	ln(Number of Granted Patents per Municipality)	-0.0017	(0.0020)	0.0019	(0.0018)
	ln(Number of Citations per Patent, 3 year citation lag)	0.0013	(0.0012)	0.0026***	(0.0009)
	ln(Number of Citations per Patent, 5 year citation lag)	0.0013	(0.0017)	0.0043***	(0.0013)
	ln(Number of Claims US)	-0.0087**	(0.0036)	-0.0054*	(0.0029)
	ln(Number of Claims Europe)	-0.0064*	(0.0033)	-0.0035	(0.0028)
	ln(Family Size)	-0.0051**	(0.0024)	-0.0045**	(0.0020)
	Number of Municipalities	392		1043	

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. A regression of the variables indicating patent quality on the continuous year variable (1990 to 1997 for the period before the reform and 1998 to 2008 for the period after the reform) provides the average changes in the outcome variable for the treatment and the control groups and for the period before and after the reform. The trends of the treatment and the control groups before the reform do not show a statistically significant difference.

3.5 Empirical Framework

To analyze the effect of the establishment of UAS on patent quality, we again exploit the quasi-natural variation in the location and time of the establishment of UAS campuses, applying the difference-in-differences method. We thereby compare our indicators of patent quality in the treated regions with the same indicators in the untreated regions. Thus to estimate the effect of UAS on patent quality, we use the following equation:

Equation 5 $$Y = \alpha + \beta Treatment_{jt} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

The explanatory variables on the right-hand side of the equation remain unchanged. As in Equation 1, TG_j indicates whether municipality j is part of the treatment group, γ contains year dummies that show the time trend common to the treatment and the control groups, λ_k includes district fixed effects, and ε_{jt} represents the error term. The coefficient β of $Treatment_{jt}$ measures the effect of UAS on the different patent quality indicators.

Instead of the number of patent applications, our dependent variable Y includes our set of indicators for patent quality in municipality j in year $t+3$. As in the baseline model, we use the natural logarithm to show the relative changes in the treatment group compared to the control group, in percent.[59] Thus Y includes the following:

- the number of granted patents in each municipality and in each year $ln(Granted_{jt+3})$;

- the citations each patent receives within three years and within five years[60], $ln(Citations\ per\ patent_{jt+3})$;

- the number of claims each patent application shows in the latest US publication, $ln(Claims\ US_{jt+3})$, and in the latest EP publication, $ln(Claims\ EP_{jt+3})$; and

- the number of jurisdiction in which a patent is protected, $ln(Family\ size_{jt+3})$

[59] In addition, the distributions of the quality indicators are positive and highly skewed to the right (see Table 18). We apply the natural logarithm to transform our outcome variables in (approximate) normal distributions.

[60] For those patent applications having no citations, we add a constant of 1 before transforming into $ln(Citations\ per\ patent_{jt+3})$

Finally, the difference-in-differences technique is particularly appropriate to measure changes in patent quality because of two reasons. First, finding a correct and meaningful benchmark, a problem that usually arises in the literature analyzing effects on patent quality, is not an issue in our study.[61] The difference-in-differences approach estimates changes in patent quality in the treatment group (areas in which UAS were established) relative to the control group (areas in which UAS were not (yet) established). The interpretation of the results is therefore straightforward, as they show changes relative to the control group.

Second, estimating changes in patent quality over time might lead to biased results: Factors that are unrelated to inventive or economic characteristics, such as changes in patent legislation or changes in the measurement technique of the quality indicators, might lead to misleading estimation outcomes. However, as these factors affect the treatment and the control group equally, they do not distort our results.

[61] Further information about problems estimating patent quality over time are given in Squicciarini et al. (2013) and OECD (2009).

3.6 Results

Figure A3 to Figure A8 and Table A1 to Table A2 show no indication for a violation of the common trends assumption.[62] Table 20 shows the results of Equation 5 using the different quality indicators. The first column displays the results for the number of granted patents per municipality. This quality indicator informs whether the quality of the patent applications in terms of the patentability criteria—inventive step, novelty, and industrial applicability—changes due to the establishment of UAS.

The coefficient of the variable $Treatment_{jt}$ equals 7.5 and is statistically significant at the one percent level. In other words, the number of granted patent applications in municipalities located in treated areas increases by 7.8 percent more than that in municipalities located in untreated areas. This increase in the number of granted patents is thus parallel to the increase in the number of patent applications found in the preceding chapter.[63] The establishment of UAS does therefore not lead to an increase in the number of patent applications that are of low quality and that never end up in granted patents. In contrast, the increase in innovation quantity is also an increase in innovation quality.

In the second and the third column of Table 20, the results for our two forward citations indicators (the second column refers to the three-year citation lag, the third to the five-year lag) appear. While the variable for granted patents shows the absolute number of granted patent applications for each municipality, our forward citation indicators show the number of citations for each patent application. These two indicators are thus relative quality measures showing the change in average citations for each patent application. The effect of UAS on forward citations with a three-year citation lag equals 1.3 percent, and the effect of UAS on forward citations with a five-year lag is 3.1 percent. Both coefficients are statistically significant.

[62] Several quality indicators show a drop in year 2007, confirming that the indicators highly correlate and thus have a common underlying notion of patent quality.

[63] The effect on the number of granted patents per patent applications, i.e., the change in the ratio of granted patents relative to the number of patent applications, equals 0.004 and is statistically insignificant.

Table 20 OLS results for patent quality

	Dependent Variable					
	ln(Granted)	ln(Citations, 3-year lag)	ln(Citations, 5-year lag)	ln(Claims US)	ln(Claims EP)	ln(Family Size)
Year	yes	yes	yes	yes	yes	yes
TG_j	0.0123	0.0160	0.0262	0.0250	0.0303	0.0164
	(0.0483)	(0.0135)	(0.0215)	(0.0637)	(0.0605)	(0.0458)
$Treatment_{jt}$	0.0747***	0.0128*	0.0301***	0.1006***	0.0887***	0.0654***
	(0.0190)	(0.0075)	(0.0104)	(0.0264)	(0.0253)	(0.0179)
Constant	0.3042***	0.0686***	0.1257***	0.5500***	0.5069***	0.3793***
	(0.0383)	(0.0115)	(0.0177)	(0.0526)	(0.0496)	(0.0373)
AR2	0.2053	0.1092	0.1362	0.1711	0.1723	0.1879
R2	0.2093	0.1137	0.1405	0.1753	0.1765	0.1920
n	22960	22960	22960	22960	22960	22960
p-Value	0.0248	0.0001	0.0000	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered Standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

This effect on the two quality indicators has three implications. First, as forward citations reflect the importance of the patented technology for the patent holder, the establishment of UAS increased the private economic value of patents for their owners. Second, citations mirror the social value of an invention, i.e., its economic externalities: A large number of forward citations implies that the invention is important for those not holding the patent. The UAS thus increased not only the private value of patents but also their social value. Third, an increase in the number of citations with a short citation lag implies that the invention is rapidly recognized. The positive effect of the number of citations with a three-year lag thus shows that UAS increased the technological value of patents.

The fifth and sixth columns show the results for the indicators number of claims in the US and in Europe. These two indicators show the boundaries of the property rights that the patent protects. More claims, i.e., a broader scope of a patent, implies a broader legally protected technological area and, consequently, higher economic value for the patent holder. In our difference-in-differences framework, the coefficient of the variable $Treatment_{jt}$ thus shows the percentage change in the number of claims per patents in the treatment group compared to that in the control group. The two indicators thus measure whether the average scope of a patent—and its economic value—in the treatment group increased relative to that of patents in the control group. Regarding the US, the effect amounts to 10.6 percent, and regarding Europe, 9.3 percent. The average number of claims per patent thus increased by almost 11 percent in the US, and by more than 9 percent in Europe. These results, therefore, demonstrate that the establishment of UAS led to a significant increase in the average patent scope and, consequently, to an increase in the average economic value of the patents.

The last column shows the change in the average patent family size, i.e., the number of countries in which a patent is protected. Given that filing and enforcing an invention in different jurisdictions is costly, only patents of high expected value have protection in several countries. In regions that received a UAS, the average patent family size increased by 6.8 percent. Thus patents in treated regions are protected in 6.8 percent more countries than patents in untreated regions are, corroborating the increase in the economic value of patents due to the establishment of UAS. Finally, given that all indicators show a positive and statistically significant effect, the establishment of UAS seems to increase not only different aspects of patent quality but also the common notion of quality.

3.7 Conclusion

While UAS increased regional innovation activities in terms of quantity, their effect on innovation quality remains unclear. Analyzing the effect of UAS on qualitative aspects of patent applications, this chapter examines whether UAS increased the quantity but decreased the quality of patents, i.e., whether a trade-off between patent quantity and quality exists. We first discuss the skewed distribution of patent value and the resulting need for further qualitative indicators to measure patent quality. We then present our qualitative indicators, namely, grant status, forward citations, claims, and patent family size, and discuss how they are related to different aspects of patent value.

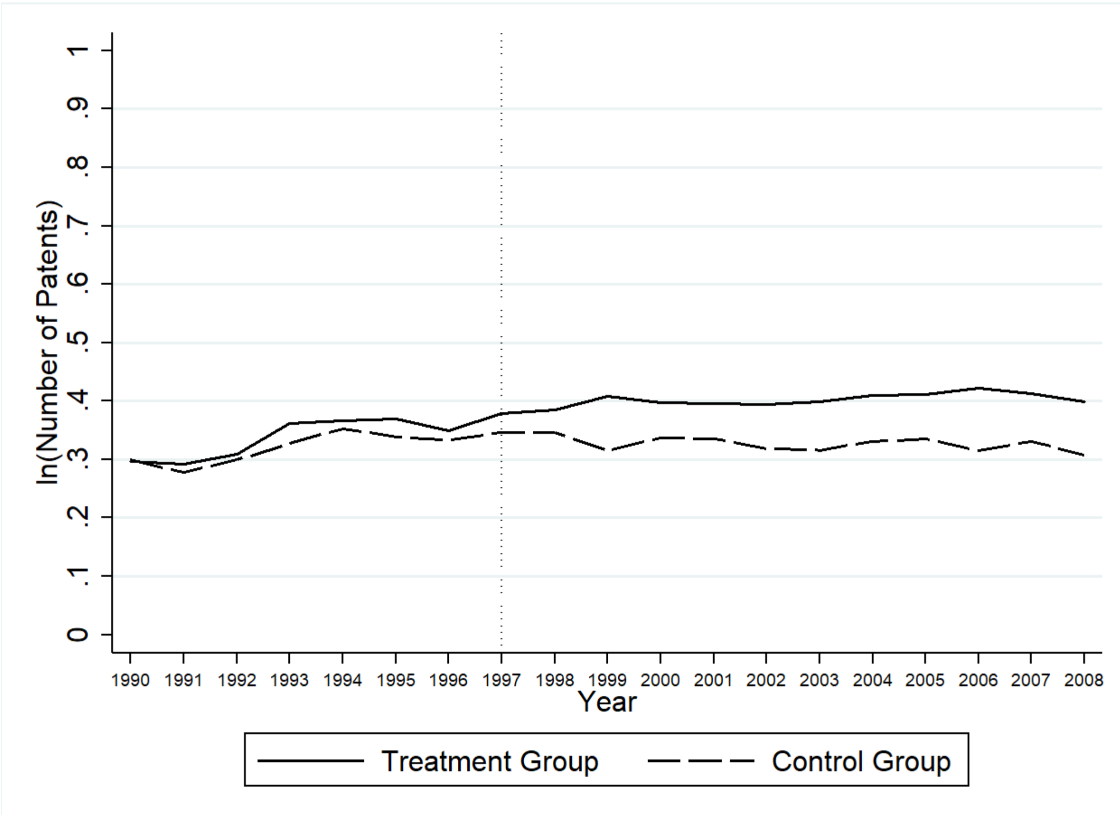
We find a positive and statistically significant effect on the number of granted patents per municipality. Thus the increase in innovation quantity is also an increase in innovation quality, as inventions that are granted fulfill the patentability criteria: inventive step, novelty, and industrial applicability. Moreover, the patent quality in the treated regions increases after the establishment of UAS campuses. The increase of 6.8 percent in the average patent family size, an indicator measuring the number of countries in which the patent is protected and thus reflecting its value, demonstrates the strong effect of the UAS establishment on patent quality in terms of economic value. The increase of 9.3 to 10.6 percent in the average number of claims, mirroring the legally protected scope of a patent, corroborates this increase in the economic value of patents.

The results for the forward citations indicators further confirm this increase in the private economic value, i.e., the value for those holding the patent. Moreover, as forward citations also measure the externalities for those not holding the patent—the patents' social value—, the results demonstrate that the establishment of UAS has led to positive externalities—technology spillovers—for those not holding the patent. Finally, as all indicators show a positive and statistically significant effect, the establishment of UAS seems to increase all aspects of the patents' economic and technological value. The establishment of UAS thus increased both, innovation quantity and quality. A trade-off between patent quantity and quality is therefore very unlikely.

The results of this chapter allow us to formulate the following policy implications: The establishment of UAS increased not only the quantity but also the quality of patents. UAS, therefore, constitute an important alternative to academic universities to increase regional innovation activities. Future research might use other data sources and focus on direct quality indicators, such as the asset value of a patent, instead of indirect measures from the patenting procedure, to investigate the effect of UAS on further patent value aspects.

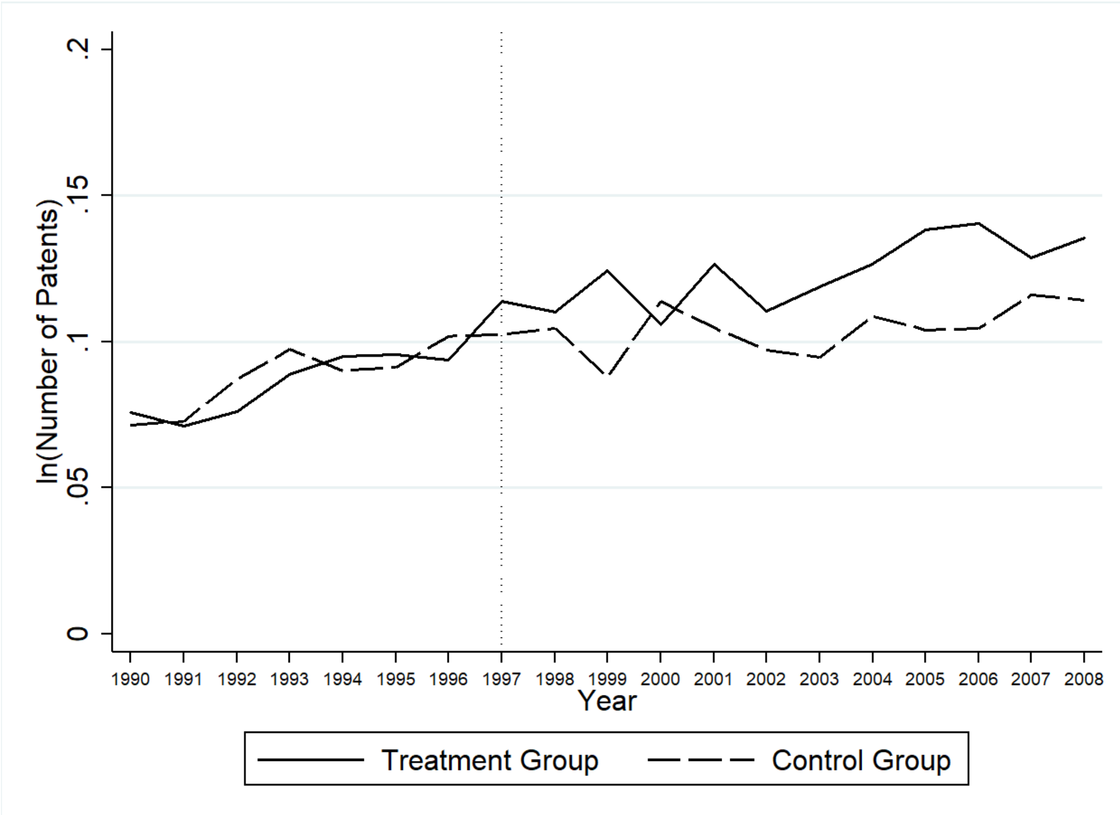
3.8 Appendix

Figure A3 ln(Number of Granted Patents) for treatment and control group, before and after UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A4 ln(Number of Citations per Patent, three-year citation lag) for treatment and control group, before and after UAS establishment

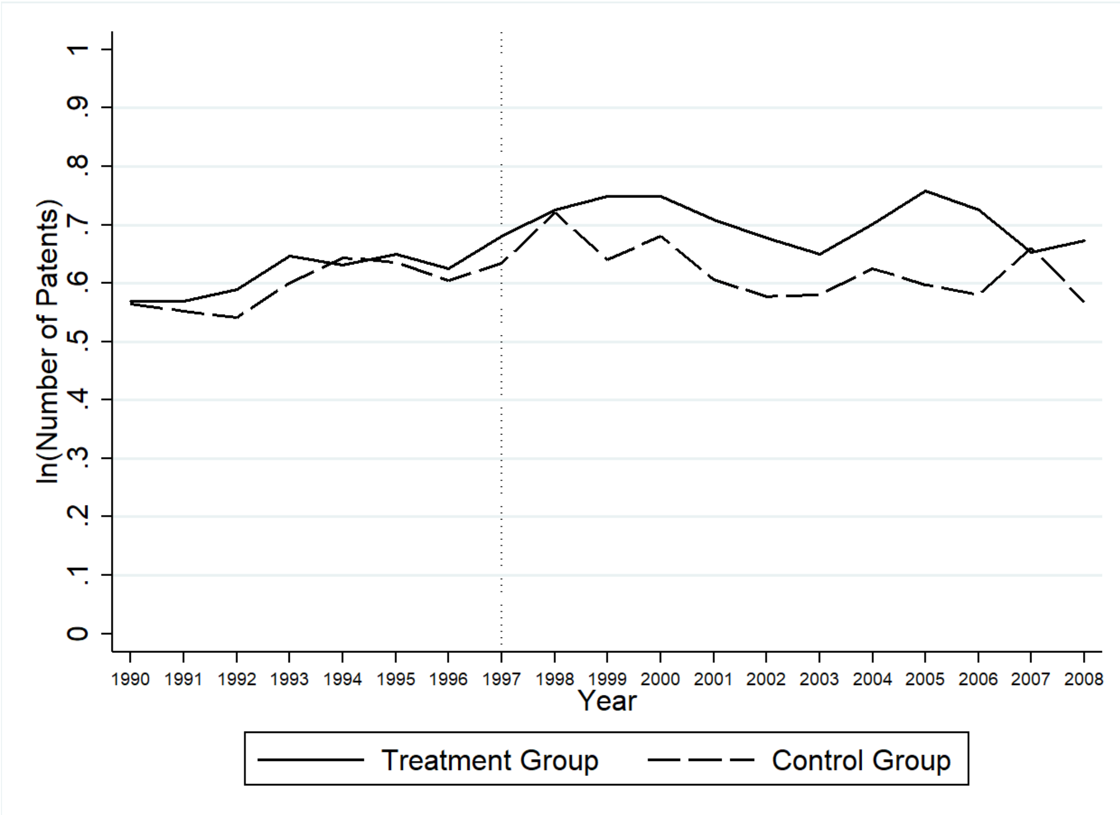


Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A5 ln(Number of Citations per Patent, five-year citation lag) for treatment and control group, before and after UAS establishment

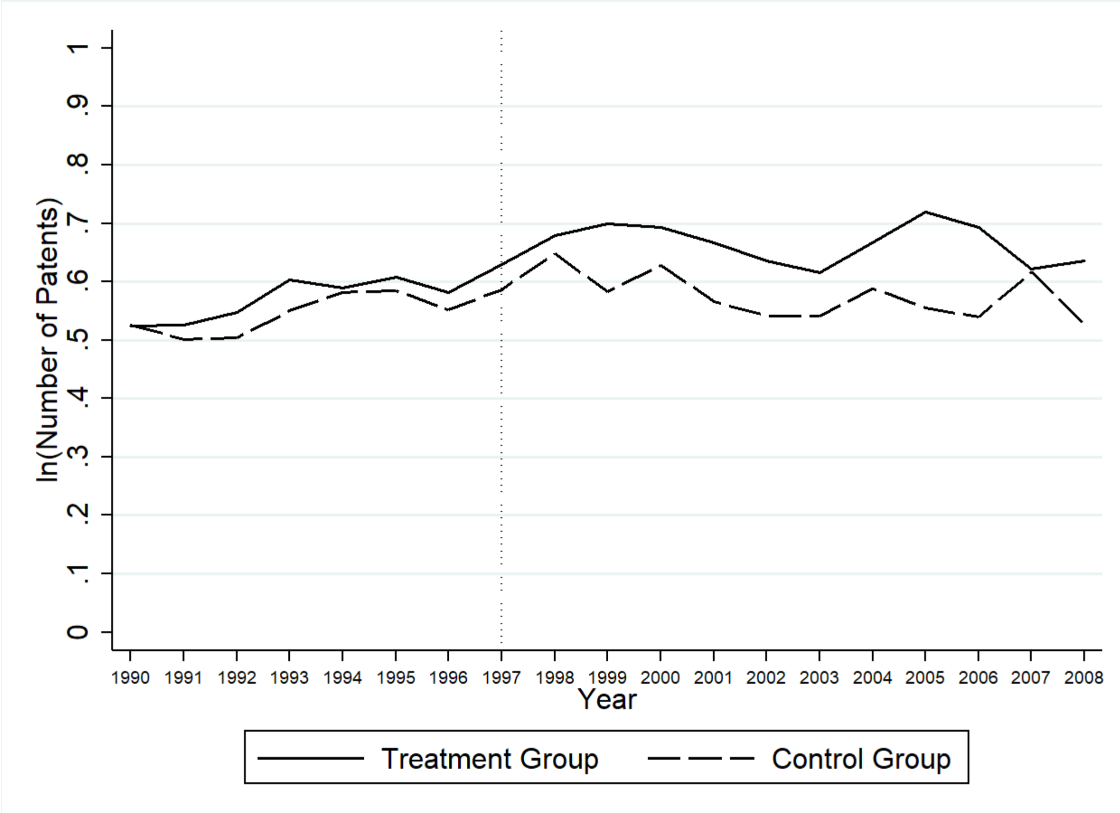
Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A6 ln(Number of Claims US) for treatment and control group, before and after UAS establishment



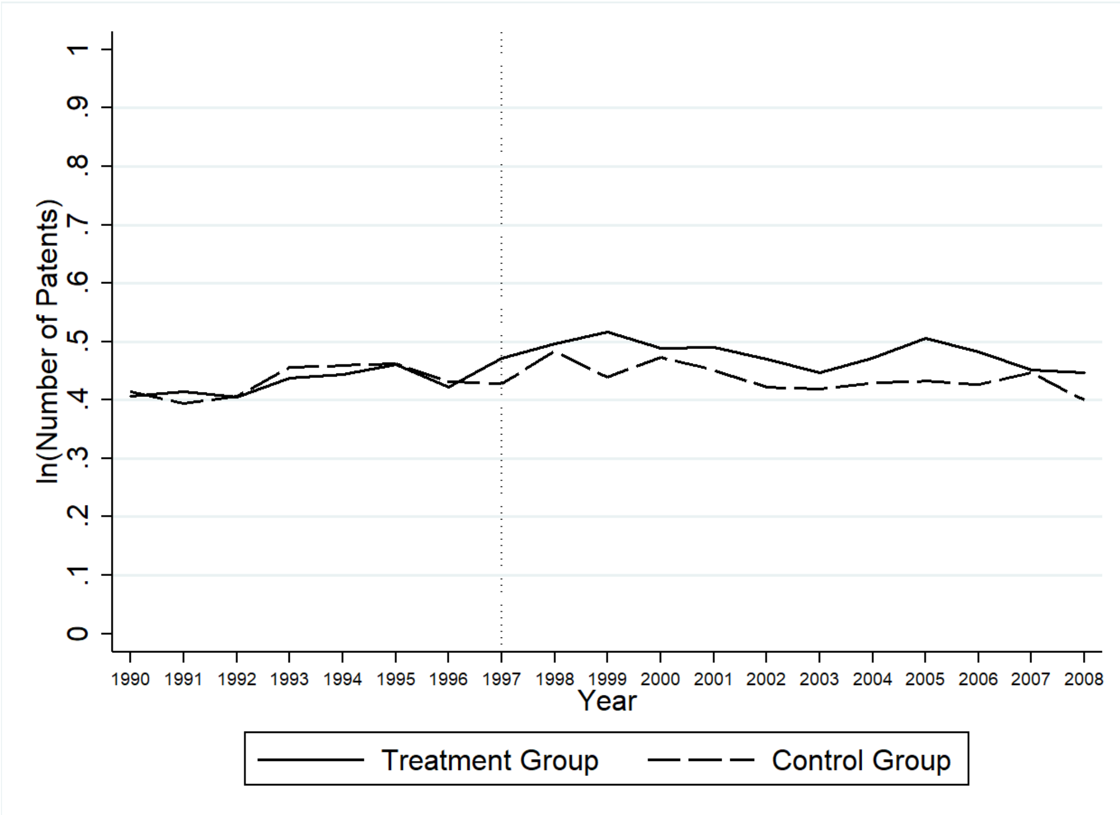
Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A7 ln(Number of Claims EP) for treatment and control group, before and after UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A8 ln(Average Family Size) for treatment and control group, before and after UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Table A1 Parallel trends assumption quality indicators – linear trend

	Dependent Variable					
	ln(Granted)	ln(Citations, 3-year lag)	ln(Citations, 5-year lag)	ln(Claims US)	ln(Claims EP)	ln(Family Size)
Year	0.0090***	0.0044***	0.0071***	0.0128**	0.0113**	0.0054
	(0.0027)	(0.0015)	(0.0021)	(0.0057)	(0.0054)	(0.0037)
Year x TG_j	0.0034	0.0009	0.0027	0.0018	0.0026	0.0025
	(0.0036)	(0.0018)	(0.0026)	(0.0070)	(0.0066)	(0.0046)
TG_j	0.1519***	0.0362***	0.0593***	0.2566***	0.2385***	0.1825***
	(0.0303)	(0.0078)	(0.0119)	(0.0451)	(0.0421)	(0.0322)
Constant	0.1453***	0.0340***	0.0615***	0.3126***	0.2890***	0.2226***
	(0.0231)	(0.0056)	(0.0088)	(0.0357)	(0.0333)	(0.0253)
AR2	0.0129	0.0080	0.0115	0.0142	0.0145	0.0151
R2	0.0131	0.0083	0.0118	0.0144	0.0147	0.0153
n	11480	11480	11480	11480	11480	11480
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered Standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A2 Parallel trends assumption quality indicators – year dummies

		Dependent Variable					
		ln(Granted)	ln(Citations, 3-year lag)	ln(Citations, 5-year lag)	ln(Claims US)	ln(Claims EP)	ln(Family Size)
Year							
	1990	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
	1991	-0.0216	0.0014	-0.0033	-0.0128	-0.0240	-0.0194
		(0.0170)	(0.0083)	(0.0117)	(0.0368)	(0.0344)	(0.0235)
	1992	0.0003	0.0158	0.0158	-0.0235	-0.0209	-0.0064
		(0.0191)	(0.0101)	(0.0136)	(0.0386)	(0.0366)	(0.0264)
	1993	0.0282	0.0259**	0.0425***	0.0360	0.0246	0.0418
		(0.0192)	(0.0124)	(0.0160)	(0.0423)	(0.0389)	(0.0288)
	1994	0.0536**	0.0186*	0.0316**	0.0793	0.0556	0.0460
		(0.0235)	(0.0112)	(0.0152)	(0.0487)	(0.0442)	(0.0316)
	1995	0.0397**	0.0199**	0.0342**	0.0710	0.0596	0.0493*
		(0.0189)	(0.0100)	(0.0144)	(0.0441)	(0.0409)	(0.0289)
	1996	0.0347*	0.0305***	0.0546***	0.0393	0.0263	0.0171
		(0.0200)	(0.0110)	(0.0163)	(0.0424)	(0.0393)	(0.0296)
	1997	0.0477**	0.0311***	0.0379**	0.0692	0.0611	0.0145
		(0.0229)	(0.0118)	(0.0160)	(0.0470)	(0.0451)	(0.0295)
Year x TG_j							
	1990	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
	1991	0.0174	-0.0061	-0.0043	0.0134	0.0259	0.0271
		(0.0222)	(0.0111)	(0.0157)	(0.0463)	(0.0433)	(0.0311)
	1992	0.0128	-0.0153	-0.0124	0.0447	0.0440	0.0048
		(0.0240)	(0.0130)	(0.0174)	(0.0494)	(0.0462)	(0.0341)
	1993	0.0375	-0.0127	-0.0100	0.0411	0.0541	-0.0099
		(0.0250)	(0.0153)	(0.0203)	(0.0527)	(0.0486)	(0.0360)
	1994	0.0169	0.0007	0.0020	-0.0175	0.0095	-0.0079

		(0.0289)	(0.0145)	(0.0195)	(0.0587)	(0.0534)	(0.0388)
	1995	0.0331	-0.0001	0.0168	0.0102	0.0236	0.0051
		(0.0256)	(0.0136)	(0.0198)	(0.0552)	(0.0512)	(0.0371)
	1996	0.0179	-0.0124	-0.0166	0.0163	0.0303	-0.0011
		(0.0266)	(0.0137)	(0.0201)	(0.0535)	(0.0495)	(0.0373)
	1997	0.0346	0.0069	0.0274	0.0424	0.0437	0.0502
		(0.0291)	(0.0152)	(0.0204)	(0.0580)	(0.0552)	(0.0376)
TG_j		0.1425***	0.0443***	0.0685***	0.2440***	0.2189***	0.1828***
		(0.0328)	(0.0099)	(0.0146)	(0.0521)	(0.0490)	(0.0369)
Constant		0.1541***	0.0314***	0.0598***	0.3249***	0.3059***	0.2237***
		(0.0255)	(0.0070)	(0.0107)	(0.0414)	(0.0391)	(0.0289)
AR2		0.0124	0.0074	0.0112	0.0135	0.0138	0.0146
R2		0.0137	0.0087	0.0125	0.0148	0.0151	0.0159
n		11480	11480	11480	11480	11480	11480
p-Value		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered Standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. For all quality indicators, results show no statistically significant effect for the joint F-test of the interaction between the year dummies and the variable *TG*.

Chapter 4

Tertiary Vocational Education and Innovation – Beneficiaries of Universities of Applied Sciences

Part of this chapter is an extended version of early parts of the working paper "Regional Effects of Applied Research – Universities of Applied Sciences and Innovation", by Pfister, Rinawi, Harhoff & Backes-Gellner, 2016.

4.1 Introduction

The results of the preceding chapters demonstrate that the establishment of UAS increased both innovation quantity and quality and that different forms of spillovers—such as UAS graduates[64]—constitute a fundamental determinant of this innovation effect. However, the question of who benefits from these spillovers remains unclear. The beneficiaries of direct spillovers (UAS graduates entering the labor market, and collaboration with UAS) and indirect spillovers (agglomeration economies) are local firms. Whether different types of them—i.e., small, medium-sized, large, or newly founded firms—profit equally from these spillovers has to be analyzed. As the literature shows large differences in innovation activities among these different types of firms (e.g., Audretsch, 2001, or Frietsch, Neuhäusler, & Rothengatter, 2013), the innovation effect induced by UAS might differ among them.

This chapter answers the question of whether the increase in innovation quantity, which we found in the preceding chapter, relates to small and medium-sized firms, to large firms, or to newly

[64] See 2.6.4 Confounding Effects: Education Expansion of Academic Universities.

founded firms. We thereby focus on the patent applicants' characteristics that are available in our patent database: this allows us to create proxies for the different types of firms and to differentiate among heavy applicants (large firms), light applicants (small and medium-sized firms), and first-time applicants (newly founded firms of firms that did not patent before the reform).

To analyze the effect of the establishment of UAS on these different types of applicants, we estimate our basic estimation equation in two different subsamples. Our first subsample excludes the heavy applicants of our patent database and shows the effect of UAS on (proxies for) small and medium-sized firms (thereby also informing about the effect on the proxies of large firms). Our results show that both, small and medium-sized and large firms increase their innovation activities. However, the effect of UAS on large firms is larger than the effect on small and medium-sized firms. Our second subsample consists of first-time applicants, i.e., applicants that appear during our observation period for the first time (including newly founded firms). Estimations using this subsample thus inform about the effect of UAS on those (new) firms that start patenting. The results show a 3.5 percent increase in the number of first-time applicants.

Spillovers of UAS may have a heterogeneous effect not only on different types of firms but also on different geographical areas. The literature shows that innovation activities are regionally clustered and that rural areas benefit less from these clusters (e.g., Acs et al., 2003, or Abel, Gabe, & Stolarick, 2014). Whether the establishment of UAS constitutes a potential mean to improve this disadvantaged situation of rural areas, i.e., whether rural areas benefit from spillovers of UAS, is a fundamental question for all countries concerned with innovation.

In the second part of the chapter, we analyze whether the establishment of UAS increased innovation activities in rural areas. We first show that compared to academic university catchment areas of equal size, UAS catchment areas have a larger share of rural municipalities. We then restrict our sample to rural municipalities and estimate whether, compared to innovation activities in those rural areas not receiving a campus, innovation activities increased in rural areas receiving a UAS campus. Our results show that the number of patent applications increased by 4.8 percent in the rural areas receiving a UAS campus.

This chapter demonstrates, at least, two important results that have fundamental policy implications. First, the results reveal which types of firms—identified by different types of applicants—profit from spillovers of UAS: While all types show an increase in their innovation activities, large firms show the biggest effect and, therefore, profit most. UAS thus generate spillovers of which all types of firms benefit and therefore constitute an effective means to foster innovation activities not only in large firms but also in small and medium-sized firms. Moreover, the increase in the number of first-time applicants indicates that UAS have an impact on newly founded firms or on firms that did not innovate before the reform. Second, all types of geographical areas profit from spillovers of UAS. As rural areas exhibit an economically significant increase in patenting activities, UAS also foster innovation outside major centers of innovation, i.e., outside metropolitan innovation clusters, and are therefore a means to improve disadvantageous economic conditions of such rural areas.

4.2 The Effect of UAS on Different Types of Applicants

The previous chapters show that the establishment of UAS increased the regional quantity and quality of innovation. Whether this effect depends on small and medium-sized, large, or newly founded firms—i.e., the question whether these different types of firms profit equally from the establishment of UAS—remains unclear. The effect might vary because these different types of firms show large differences in their innovation activities.[65]

On the one hand, firm size seems to be an important factor in determining the number of patents produced by a firm. Many authors showed that the majority of patent filings relate to large firms; thus, patent applications are highly skewed in terms of firm size (see, e.g., Frietsch, Neuhäusler, & Rothengatter, 2013; Blind, Edler, Frietsch, & Schmoch, 2006; Frietsch & Jung, 2009; Hingley, & Bas, 2009). Similar to these findings of the literature, our sample shows that few applicants are responsible for the large majority of patent applications: Table 21 shows the descriptive statistics regarding the applicants and their respective number of patent applications in our sample. The median applicant possesses three patent applications, and the mean applicant possesses almost 32 applications. Given this large difference between the mean and the median, the distribution of applicant size is highly skewed to the right.

Table 21 Descriptive statistics on applicant size

Variable	Patent Applications per Applicant
Mean	31.81
Median	3.00
SD	446.71
Min	0.14
Max	29603.83
N	11693

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version.

[65] The differences in patenting activities between large firms and small and medium-sized firms might relate to their available resources, such as economies of scale and economies of scope, research facilities, size of research teams, firm attractiveness for highly skilled workers, resources to file, to commercialize, and to defend an invention, as well as strategic objectives of patenting (e.g., Frietsch et al., 2013; Schettino & Sterlacchini, 2009).

On the other hand, although small and medium-sized firms appear less in patent databases than large firms do, the literature emphasizes their importance. The literature shows that they are able to respond quickly and flexibly to market needs due to their organizational advantage; they, therefore, constitute an important rejuvenation factor of the economy and essentially contribute to growth and innovation (e.g., Audretsch, 2001; Frietsch et al., 2013). The literature furthermore shows that entrepreneurial activities—the creation of new firms, such as start-ups that mostly constitute small and medium-sized firms—correlate with innovative activities; moreover, entrepreneurial and innovative activities build geographic clusters (see, e.g., Chaterji, Glaeser & Kerr, 2013).

4.2.1 The effect of UAS on Heavy Applicants

Given the differences between these firms and the resulting heterogeneity in innovation activities, the effect of the establishment of UAS on them might also differ.[66] We investigate whether this effect differs among small and medium-sized firms, large firms, and newly founded firms, using different subsamples of patent applicants that function as a proxy for them.[67] In our first subsample, we focus on heavy applicants that are responsible for the majority of patent applications, a proxy for large firms, and investigate whether innovative activities of these heavy applicants increase even more due to the establishment of UAS. We identify these heavy applicants as follows: First, we calculate the number of patent applications for each applicant. Second, we restrict our sample such that each applicant appears only once in the database and calculate the cumulative distribution of these applicants according to the number of patent applications they are

[66] The establishment of UAS might affect the innovative (and entrepreneurial) activities of all these firms, because collaboration with UAS increase their patenting activities or results in newly founded firms. In addition, UAS graduates constitute valuable members of the R&D teams of all these different types of firms: UAS include both vocational and academic education, and their teaching and research focus on applied R&D; their graduates therefore acquire not only scientific and practical knowledge, but also the skills to transfer this knowledge into practice.

[67] Matching our patent database with employer data including information on the size of the firm would allow us to identify whether an applicant constitutes a) a legal entity and b) a small, a medium-sized, or a large firm. However, such employer data is not available. We therefore identify firms in the patent database using the applicants' names, focusing on all forms of legal entities. More than 62 percent of all applicants in our patent database appear as a legal entity. We then assume that the top percentile in terms of applicant size, i.e. the heavy applicants, are large firms. Results show that almost all the heavy applicants (96 percent) are legal entities.

holding. Third, we focus on the long right tail of the skewed applicant size distribution and identify the applicants in the upper percentile, the upper five percentiles, and the upper decile.

To test whether the establishment of UAS changed the heavy applicants' innovative activities, we proceed as follows: In a first specification, we identify all patent applications held by the upper percentile, i.e., the heavy applicants, in our sample. These heavy applicants are responsible for 62 percent of all patent applications in our sample. We then exclude these patent applications held by the upper percentile and estimate Equation 1 from the baseline model. The resulting change in the innovation effect reveals whether heavy (large firms) or light applicants (small and medium-sized firms) benefit from the UAS establishment: A decrease in the coefficient of $Treatment_{jt}$ indicates that the heavy applicants, whose patent applications are excluded from the sample, are the main drivers of the effect. An increase in the coefficient implies that the remaining 99 percent of the applicants, whose patent applications are not excluded from the sample, are responsible for the increase in innovation. Thus excluding the heavy applicants (and their respective patent applications) from the sample informs about the effect of UAS not only on these heavy applicants but also on the light applicants. In a second and a third specification, we exclude the upper five percent and the upper ten percent of the heavy applicants and investigate how the effect of the UAS establishment on innovation changes.[68]

Equation 1 $$ln(Number\ of\ patents_{jt+3}) = \alpha + \beta Treatment_{jt} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

Figure A9 to Figure A11, and Table A3 to Table A4 show no indication for a violation of the common trends assumption. The first column of Table 22 shows the results of the baseline model, the second column the results of the specification that excludes the highest percentile of the applicant size distribution—the heavy applicants—and their respective patent applications. The coefficient of the variable $Treatment_{jt}$ in the second column equals 8.3 percent and is almost 5 percentage points lower than the coefficient of the baseline model (13.0 percent). The third column excludes the upper five percent of the applicants. The effect of the UAS establishment equals 6.1 percent and is 7 percentage points lower than the effect of the baseline model. Finally, column four

[68] The upper five percent of the applicant size distribution have 81 percent of all patent applications, the upper decile have 87 percent of all applications.

shows the results of the subsample without the upper ten percent of the applicants. The results are almost identical to the specification in column three.

The first and the second specifications show the largest reduction of the innovation effect induced by the UAS establishment. The results, therefore, demonstrate that the heaviest five percent of the applicants, which are likely to be large firms, benefit most from the establishment of UAS. However, the innovation effect attributable to the remaining 95 percent of the applicants still equals 6 percent and is, thus, substantial. The first specification furthermore informs about the innovation effect at the intensive margin: 91 percent of these heaviest applicants that we exclude in this specification already existed before the UAS establishment; thus, heavy applicants that already innovated before the UAS reform innovate even more after the reform.[69]

[69] Of the upper fifth and the upper tenth percentiles, 74 and 68 percent of the applicants already existed before 1997; specifications two and three therefore allow no conclusions regarding the effect at the extensive margin.

Table 22 OLS results for ln(Number of Patents), without top one, five, and ten percentiles of applicants

	Dependent Variable ln(Number of Patents)			
	(1) Baseline model	(2) Without top percentile	(3) Without top 5 percentiles	(4) Without top 10 percentiles
Year	yes	yes	yes	yes
TG_j	0.0718	0.0639	0.0248	0.0123
	(0.0706)	(0.0646)	(0.0437)	(0.0341)
$Treatment_{jt}$	0.1223***	0.0800***	0.0594***	0.0563***
	(0.0266)	(0.0232)	(0.0172)	(0.0140)
Constant	0.4507***	0.4275***	0.3599***	0.3114***
	(0.0546)	(0.0499)	(0.0348)	(0.0283)
AR2	0.2513	0.2453	0.2257	0.2185
R2	0.2551	0.2492	0.2296	0.2225
n	22960	22960	22960	22960
p-Value	0.0000	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

4.2.2 The Effect of UAS on First-Time Applicants

In our second subsample, we focus on first-time applicants, i.e., applicants that appear in our database only after the establishment of UAS. These new applicants are either new firms—e.g., start-ups—that patent or already existing firms that started patenting due to the establishment of UAS. In addition, the large majority of these first-time applicants possess very few patents and are therefore likely to be small and medium-sized firms.[70] This subsample of first-time applicants thus shows the effect of the establishment of UAS on both regional entrepreneurial activities and on the innovative activities of small and medium-sized firms. To estimate the effect of the establishment of UAS on the number of first-time applicants, we proceed as follows: In the first step, we mark the year in which an applicant appears for the first time in our patent database. In the second step, we count the number of these new applicants in each year and in each municipality for all the years between 1990 and 2008 and then estimate the following estimation equation:

Equation 6
$$ln(Number\ of\ new\ applicants_{jt+3}) = \alpha + \beta Treatment_{jt} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

The variable *ln(number of new applicants*$_{jt+3}$*)* includes the natural logarithm of the number of new applicants in municipality j in year $t+3$. To show the relative changes between the treatment and the control groups in the number of first-time applicants in percent, we use the natural logarithm of the number of first-time applicants. As in the baseline model, we assume that the establishment of UAS has a lagged effect on first-time applicants and therefore assume a time lag of three years. The remaining variables γ_t, TG_j, λ_k, and ε_{jkt} are identical to the baseline model and show the common time trend, treatment group, district fixed effects, and the error term. The variable $Treatment_{jt}$ shows the average increase in the number of first-time applicants in percent due to the establishment of UAS.

[70] Frietsch et al. (2013) argue that applicants having less than three patents are small and medium-sized firms. In our data, more than 56 percent of the first-time applicants appearing after the establishment of UAS possess less than three patents. Very few applicants—less than 7 percent—are in the upper decile of the distribution of applicant size.

Figure A12, Table A5 and Table A6 in the Appendix suggest that the common trends assumption seems to hold. Table 23 shows the results of Equation 6. The coefficient of our variable of interest $Treatment_{jt}$ equals 3.5 percent.

Given the increase in the number of first-time applicants, the establishment of UAS leads to both new firms that innovate and already existing firms, such as small and medium-sized firms, which start innovating.[71] UAS, therefore, have a positive effect on entrepreneurial activities and on the innovative activities of small and medium-sized firms. In addition, as the subsample analysis includes only applicants that appear after the UAS reform, the results show the effect of the establishment of UAS on regional innovation activities at the extensive margin.

Table 23 OLS results first-time applicants

	Dependent Variable ln(Number of first-time Applicants)
Year	Yes
TG_j	0.0067 (0.0172)
$Treatment_{jt}$	0.0347*** (0.0093)
Constant	0.1511*** (0.0163)
AR2	0.1808
R2	0.1849
n	22960
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

[71] Future research might focus on composition effects. Although we can show that they do not affect our results, we cannot completely exclude them: The moving behavior of firms that innovated before the UAS establishment, which is one aspect of the composition effects, does not affect our results. Before the establishment of UAS, 0.6 percent of the applicants moved from a control group region to a treatment group region. After the establishment of UAS, this ratio reduced to 0.3 percent. However, we did not observe these firms' location before they start patenting. The question whether new applicants that did not invent before the establishment of UAS might have moved from a control group region to a treatment group region thus remains unanswered.

4.3 The Effect of UAS on Rural Areas

The literature shows that the transfer of new knowledge and technologies is highly sensitive to distance;[72] thus, innovation activities are spatially distributed and build regional clusters (see, e.g., Acs et al, 2003; Almeida & Kogut, 1999; Chatterji, Glaeser & Kerr, 2013; Paci & Usai, 1999; Jaffe, Trajtenberg & Henderson, 1993; Verspagen & Schoenmakers, 2004). Cities constitute an important role of such innovation clusters because they possess—among many other characteristics—factors, such as skilled labor, a good transport system, or educational institutions; the availability, proximity and concentration of these factors in cities enable firms to innovate.[73] This spatial distribution of innovation activities exists also in Switzerland: The correlation between the natural logarithm of the number of patent applications and the municipalities' population equals 0.611.[74] As highly populated municipalities, i.e., metropolitan areas, exhibit a larger number of patent applications, innovation also seems to appear in clusters in Switzerland.

As innovation appears in clusters and is sensitive to distance, rural areas that are not located near cities benefit less from metropolitan innovation clusters. The literature shows vast empirical evidence that rural areas have less highly educated workers, weaker economic growth rates, higher poverty, and lower innovative performance (see, e.g., Abel et al., 2014; Partridge, Rickman, Ali, & Olfert, 2009; Partridge & Rickman, 2008; Usai, 2011).

[72] Acs et al. (2003) refer to Polany (1996), Dosi, (1988), and Feldman (1994) and argue that due to the complexity, uncertainty and non-codifiable nature of highly valuable technological knowledge, the only way to transfer this knowledge is through personal interactions.

[73] Many authors highlight the importance of metropolitan areas regarding innovation activity (see, e.g., Carlindo, Chaterjee, & Hunt, 2007; Feldman & Audretsch, 1999; O hUallachain, 1999), and the reasons are manifold. Athey, Nathan, Webber, and Mahroum (2014) provide an overview of factors of an urban innovation system and emphasize the following five: firms, markets, assets (such as a good transport infrastructure, or the availability of skilled labor), institutions (e.g. educational institutions), and networks. Johnson (2014) adds demand side arguments: Due to the availability of individuals with higher wages, the consumer demand is higher and more differentiated. Chatterji et al. (2013) additionally highlight breakthrough inventions, star scientists, immigrants, the mix of small and large firms, and universities that constitute important drivers of innovation, referring to Duranton (2007), Zucker, Darby, and Brewer (1998), Agrawal, Cockburn, Galasso and Oettl (2014), Hausman (2012), Moretti (2004), Glaeser & Saiz (2004).

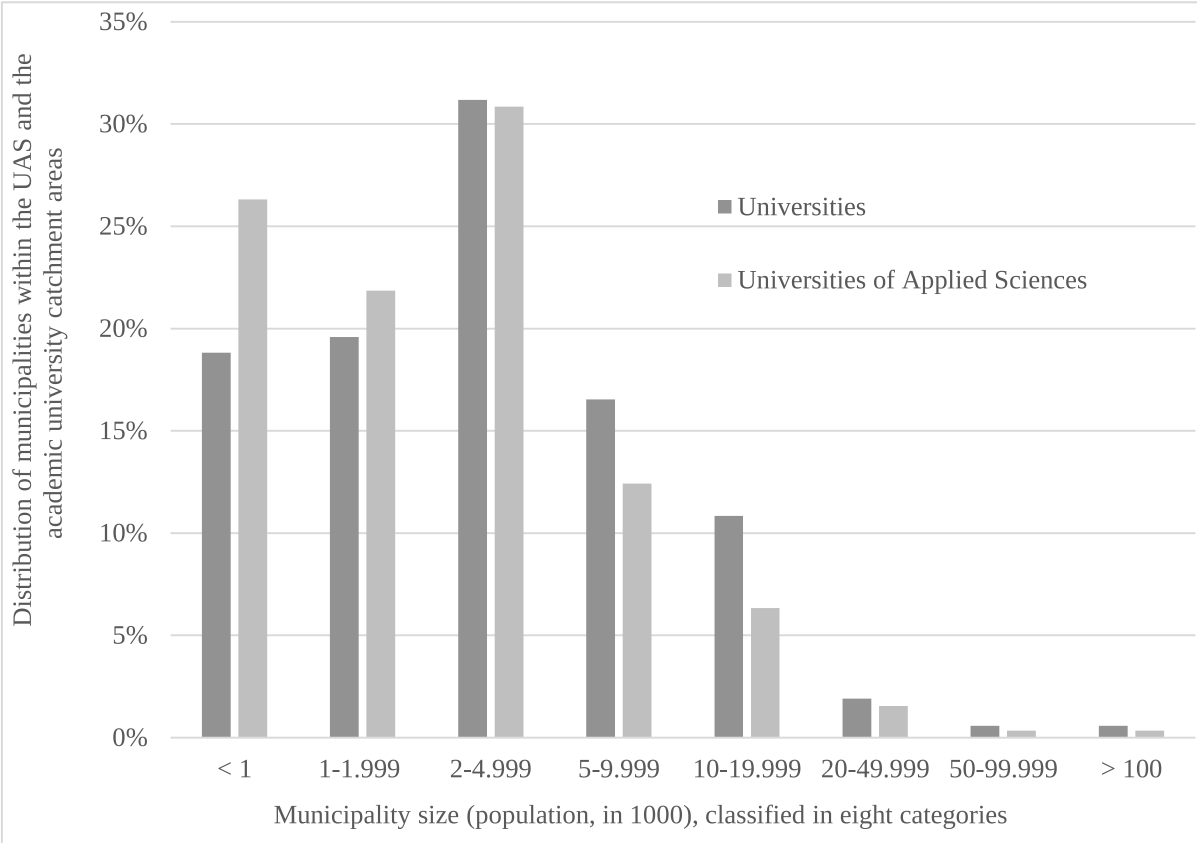
[74] We use data provided by the SFSO (Die Raumgliederung der Schweiz: Gemeindestand 01.01.2015). This data relies on STATPOP, a full survey from 2013, and includes eight categories for the municipalities' population: the first category involves municipalities that have less than 1'000 inhabitants; the second municipalities with a population between 1'000 to 1'999; the third municipalities with 2'000 to 4'999; the fourth municipalities with 5'000 to 9'999; the sixth municipalities with 10'000 to 19'999; the seventh municipalities with 50'000 to 99'000; finally, the tenth includes cities with more than 100'000 inhabitants.

The establishment of UAS constitutes a policy intervention that potentially improves the rural areas' economic conditions. The establishment of UAS aimed at revitalizing and strengthening the economy not only in metropolitan areas but also across Switzerland and was targeted particularly towards small and medium-sized firms and decentralized economies (Botschaft Fachhochschulgesetz, 1994). Thus the law governing the UAS should create a close relationship between UAS and the local economy (see, e.g., Bund-Kantone Hochschullandschaft 2008, 2004; SBFI, 2015). In addition, the federal government required that UAS campuses were equally distributed across Switzerland. UAS catchment areas, therefore, encompass a large part of rural areas: Approximately 50 percent of municipalities located within a 25-kilometer radius from a UAS campus have less than 2'000 inhabitants; Figure 6 shows that this share of sparsely populated municipalities in comparable catchment areas of conventional academic universities is ten percentage points lower.[75] Similarly, the average share of rural municipalities located in UAS catchment areas equals 57 percent, whereas the average share of the same municipalities located in conventional academic university catchment areas equals 43 percent.[76] Thus this equal distribution of UAS across Switzerland, the law governing the UAS—i.e., the combination of scientific and vocational skills taught at UAS and the focus on applied R&D—and the resulting relation to the local economy potentially lead to an improvement of the rural municipalities' economic and innovative performance.

[75] We constructed campus areas for the conventional academic universities in the German-speaking area of Switzerland (i.e., in Zurich, Lucerne, St. Gallen, Bern, and Basel) using the same 25-kilometer radius and using the same distance measure as for the construction of UAS campus areas.

[76] The SFSO differentiates between nucleated cities, agglomeration municipalities, isolated cities, and rural municipalities: this differentiation takes into account the municipalities' demography (and demographic development), structurally spatial context, employment share, economic structure, and their commuter flows to core areas. For further information, see Schuler, Dessemontet, Joye, Perlik, and Geiser (2005).

Figure 6 Distribution of municipality size for UAS and university catchment areas



Source: Authors' calculations, based on SFSO (2015).

To test whether the establishment of UAS had a positive effect on the innovation activities of rural areas, we restrict our sample to rural municipalities. Of these 887 municipalities, almost 63 percent are part of the treatment group.[77] Figure A13 shows that municipalities in these treatment groups exhibit the same trends as municipalities located in control group regions do. In addition, Table A7and Table A8 show no statistically significant differences between the trends of the treatment and the control group for both the linear and yearly trend specifications. Table 24 shows the results of Equation 1 using the sample restricted to rural municipalities.

Equation 1 $$ln(Number\ of\ patents_{jt+3}) = \alpha + \beta Treatment_{jt} + \gamma_t + \delta TG_j + \lambda_k + \varepsilon_{jt}$$

[77] In the control group, rural municipalities are, e.g., Weesen and Wattwil, in the treatment group, the rural municipalities are, e.g., Kaltbrunn and Degersheim (St. Gallen).

The coefficient of the variable *Treatment*$_{jt}$ equals 4.7, i.e., 4.8 percent and is statistically significant at the ten percent level. Thus in comparison to rural municipalities not located near a UAS campus, rural municipalities that are near a UAS campus show a 4.8 percent increase in patenting activities. The establishment of UAS, therefore, had a positive effect on rural areas and improved their innovative performance.[78]

Table 24 OLS results rural areas

	Dependent Variable ln(Number of Patents)
Year	yes
TG_j	0.0849
	(0.0614)
$Treatment_{jt}$	0.0470*
	(0.0259)
Constant	0.1498***
	(0.0415)
AR2	0.1694
R2	0.1754
n	14320
p-Value	0.1712

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

[78] Estimating the effect of the UAS on agglomeration municipalities reveals an 18.4 percent increase in patenting activities. Although comparing the effect of the UAS on agglomeration municipalities with the effect on rural municipalities can lead to misleading conclusions, as the results of the two estimations are based on different subsamples, the differing sizes of the effects indicate that rural municipalities profit less from the UAS establishment than agglomeration municipalities do.

4.4 Conclusion

The establishment of UAS has led to spillovers, such as UAS graduates entering the labor market or the collaboration between UAS and firms. This chapter answers the question whether different types of applicants, which constitute (proxies for) different types of firms, and rural areas benefited equally from such spillovers. In the first part of the chapter, we examine who profited from the establishment of UAS, focusing on different types of applicants that constitute proxies for small and medium-sized firms, large firms, and newly founded firms. We first show that innovation activities differ among these firms and that UAS, therefore, might affect them differently. To investigate this heterogeneity of the establishment of UAS, we estimate our basic estimation equation in two different subsamples. The first subsample shows whether UAS had an effect on the innovation activities of heavy applicants, i.e., the proxies for large firms. The results show that heavy and light applicants (i.e., large firms and small and medium-sized firms), profit from UAS. However, the effect on the heavy applicants is larger. The second subsample includes first-time applicants and informs about the effect of UAS on firms that did not patent before the establishment of UAS campuses or on newly founded firms that patent. The results show a 3.5 percent increase in the number of these first-time applicants.

The results using the two different subsamples furthermore show that the establishment of UAS increases innovation activities at both the intensive and the extensive margin. The innovation increase in heavy applicants reveals the effect of UAS at the intensive margin: Firms that already patented before the UAS reform produce even more patents after the establishment of UAS. The increase in the number of first-time applicants demonstrates the effect at the extensive margin: Firms that did not patent (or exist) before the UAS reform start patenting after the establishment of UAS.

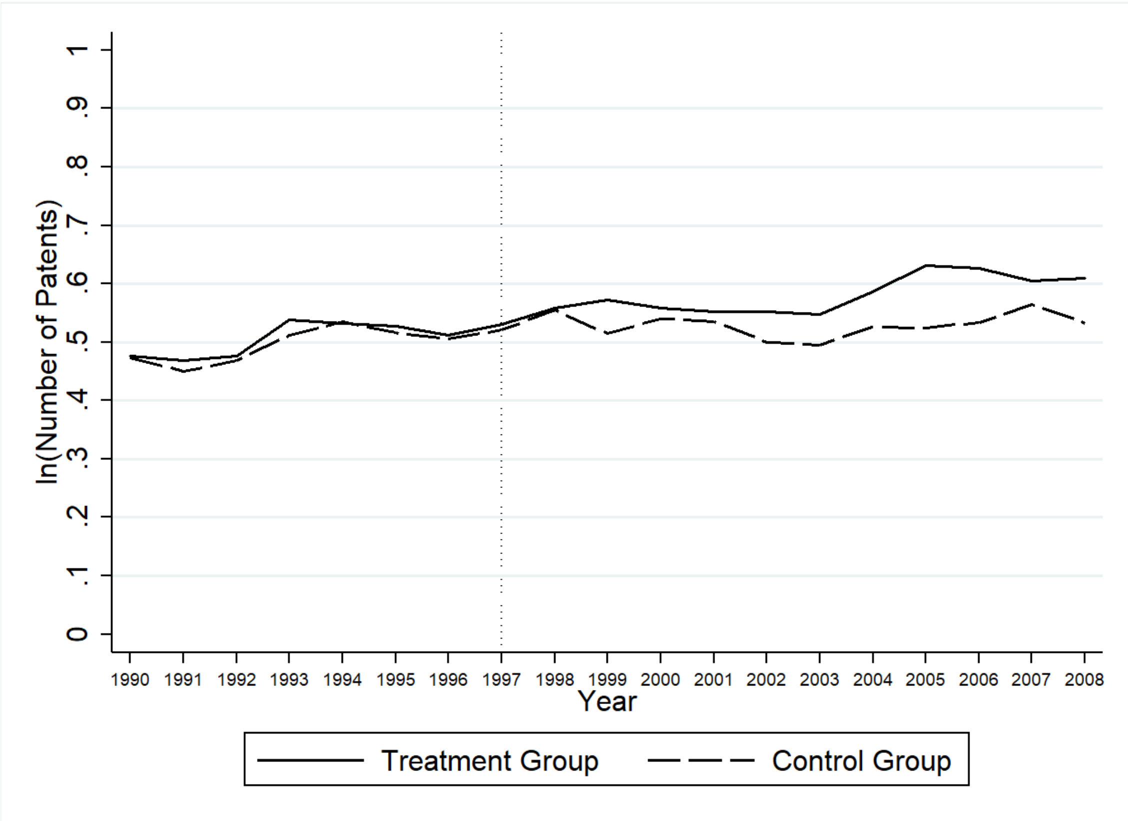
In the second part of the chapter, we answer the question regarding who profited from the establishment of UAS, focusing on rural areas. The literature shows that innovation activities build regional clusters, from which rural areas benefit less than metropolitan areas do. We first show that UAS campuses are located in relatively rural areas, as their catchment areas have a higher share of rural municipalities than academic university catchment areas have. Second, we restrict our sample to rural municipalities and estimate our basic estimation equation. This specification allows us to measure the innovation effect on rural municipalities in the treatment group relative to the innovation effect of the same municipalities in the control group. Our results show that the rural areas in the treated regions increase their innovation activities by 4.8 percent due to the establishment of UAS.

The results of this chapter allow us to formulate the following policy implications: The beneficiaries of the UAS establishment are all types of applicants and—assuming that heavy, light and first-time applicants are valid proxies for large firms, small and medium-sized firms, and newly founded firms—on all types of firms. UAS thus have an impact on both small and medium-sized firms and large firms and seem to increase regional entrepreneurial activities. The policy reform, therefore, fulfills its objective of revitalizing and strengthening firms—particularly the small and medium-sized—of the local economy. Similarly, the reform succeeds in fostering innovation in decentralized economies, as the establishment of UAS has increased innovation activities in rural areas and therefore has improved innovative performance outside metropolitan innovation clusters.

However, some questions remain unanswered and should be investigated using other data sources: First, future research might match employer data with the patent database to investigate why firms of different size are affected differently by the establishment of UAS. Possible factors causing these differences might be differences in the availability of resources or in the composition of R&D teams. Second, future research might use employer data to measure the effect of the establishment of UAS on regional entrepreneurial activities. The measure we use in our study, the number of first-time applicants, is a proxy for entrepreneurial activities and does not differentiate between newly founded firms and firms that did not patent before; in addition, the measure excludes those firms that might have been founded due to the establishment of UAS but that do not patent. Third, future research should investigate whether UAS constitute a means to overcome economic disparities between metropolitan and rural areas.

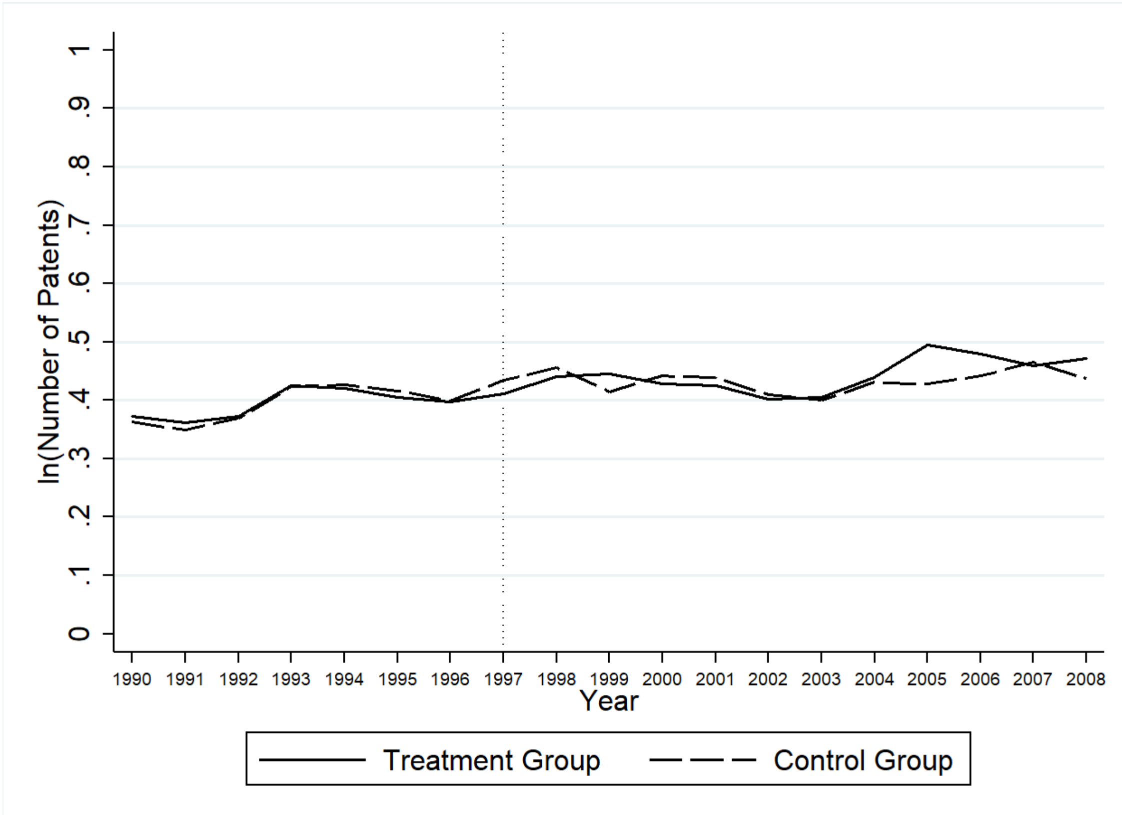
4.5 Appendix

Figure A9 ln(Number of Patents) for treatment and control group, before and after UAS establishment, without top percentile of applicants and respective patent applications



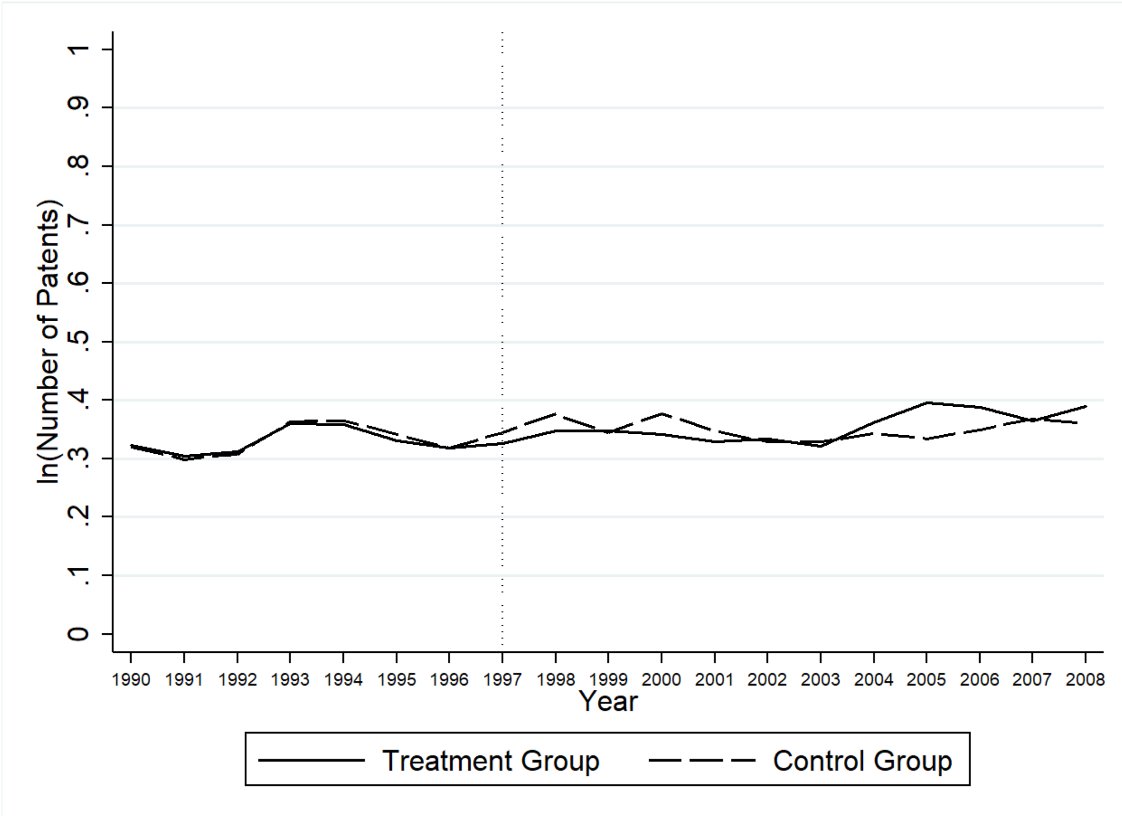
Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A10 ln(Number of Patents) for treatment and control group, before and after UAS establishment, without top five percentiles of applicants and respective patent applications



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Figure A11 ln(Number of Patents) for treatment and control group, before and after UAS establishment, without top ten percentiles of applicants and respective patent applications



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Table A3 Parallel trends assumption without top one, five, and ten percentiles of applicant and respective patent applications – linear trend

	Dependent Variable ln(Number of Patents)		
	(1) Without top percentile	(2) Without top 5 percentiles	(3) Without top 10 percentiles
Year	0.0093**	0.0107***	0.0045
	(0.0039)	(0.0037)	(0.0032)
Year x TG_j	-0.0005	-0.0041	-0.0028
	(0.0049)	(0.0046)	(0.0041)
TG_j	0.2219***	0.1825***	0.1562***
	(0.0439)	(0.0330)	(0.0285)
Constant	0.2551***	0.1904***	0.1669***
	(0.0337)	(0.0241)	(0.0205)
AR2	0.0118	0.0105	0.0100
R2	0.0121	0.0107	0.0103
n	11480	11480	11480
p-Value	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

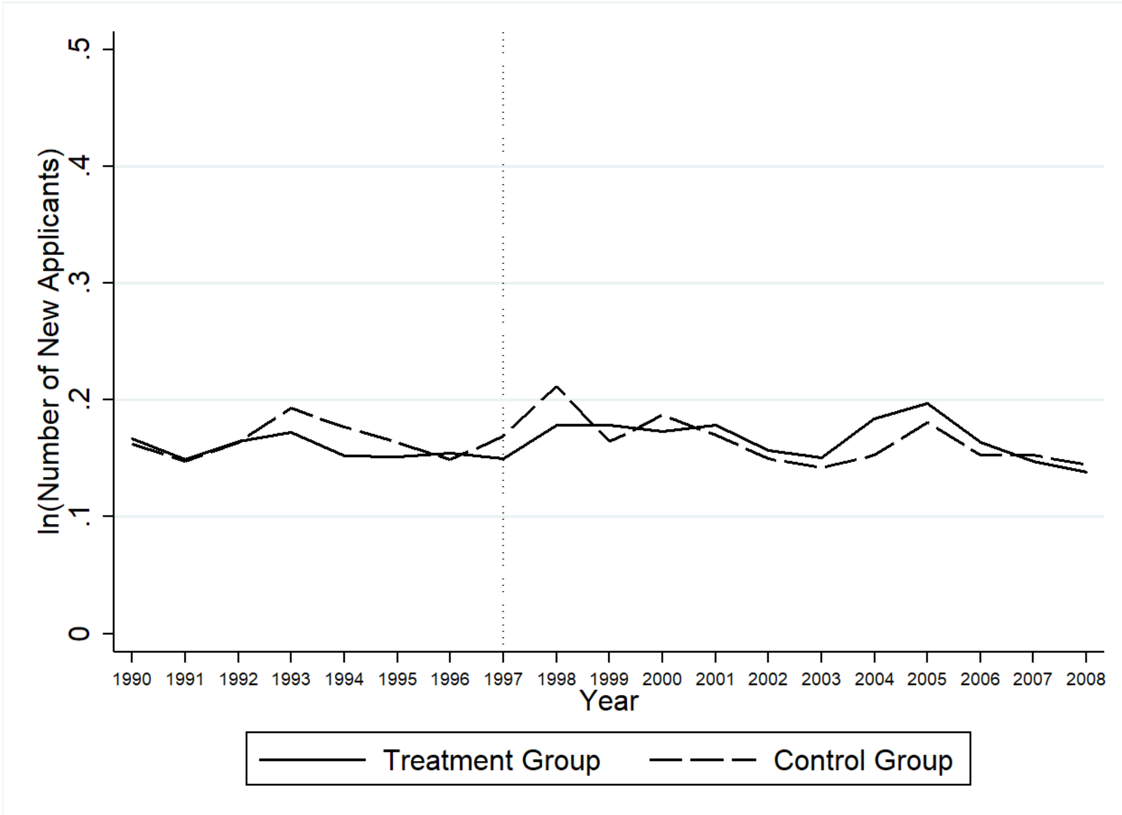
Table A4 Parallel trends assumption without top one, five, and ten percentiles of applicant and respective patent applications – year dummies

	Dependent Variable ln(Number of Patents)		
	(1) Without top percentile	(2) Without top 5 percentiles	(3) Without top 10 percentiles
Year			
1990	Base Group	Base Group	Base Group
1991	-0.0229	-0.0137	-0.0210
	(0.0228)	(0.0207)	(0.0207)
1992	-0.0037	0.0058	-0.0114
	(0.0256)	(0.0243)	(0.0231)
1993	0.0389	0.0605**	0.0440
	(0.0291)	(0.0291)	(0.0286)
1994	0.0622*	0.0634**	0.0454
	(0.0323)	(0.0305)	(0.0297)
1995	0.0433	0.0535*	0.0227
	(0.0271)	(0.0276)	(0.0259)
1996	0.0326	0.0366	-0.0020
	(0.0291)	(0.0285)	(0.0253)
1997	0.0482	0.0710**	0.0258
	(0.0313)	(0.0298)	(0.0278)
Year x TG_j			
1990	Base Group	Base Group	Base Group
1991	0.0154	0.0022	0.0021
	(0.0294)	(0.0278)	(0.0274)
1992	0.0046	-0.0060	0.0006
	(0.0322)	(0.0307)	(0.0296)
1993	0.0234	-0.0085	-0.0066
	(0.0353)	(0.0348)	(0.0343)
1994	-0.0059	-0.0147	-0.0102
	(0.0385)	(0.0365)	(0.0355)
1995	0.0077	-0.0203	-0.0152
	(0.0347)	(0.0344)	(0.0325)
1996	0.0023	-0.0115	-0.0032
	(0.0368)	(0.0356)	(0.0326)
1997	0.0065	-0.0327	-0.0227
	(0.0386)	(0.0367)	(0.0344)
TG_j	0.2135***	0.1796***	0.1533***
	(0.0478)	(0.0377)	(0.0338)

Constant	0.2628***	0.1931***	0.1697***
	(0.0374)	(0.0286)	(0.0255)
AR2	0.0112	0.0100	0.0099
R2	0.0125	0.0113	0.0112
n	11480	11480	11480
p-Value	0.0000	0.0000	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Results of the joint F-test for the interaction between the year dummies and the variable TG equal 0.9812 for the sample without top 1 percentile of applicants, 0.9902 for the sample without the top 5 percentiles, and 0.9955 for the sample without the top 1 decile (Prob. > F).

Figure A12 ln(Number of first-time Applicants) for treatment and control group, before and after UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Table A5 Parallel trends assumption first-time applicants – linear trend

	Dependent Variable ln(Number of Patents)
Year	0.0005
	(0.0023)
Year x TG_j	-0.0023
	(0.0029)
TG_j	0.0796***
	(0.0176)
Constant	0.0842***
	(0.0122)
AR2	0.0048
R2	0.0051
n	11480
p-Value	0.0000

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

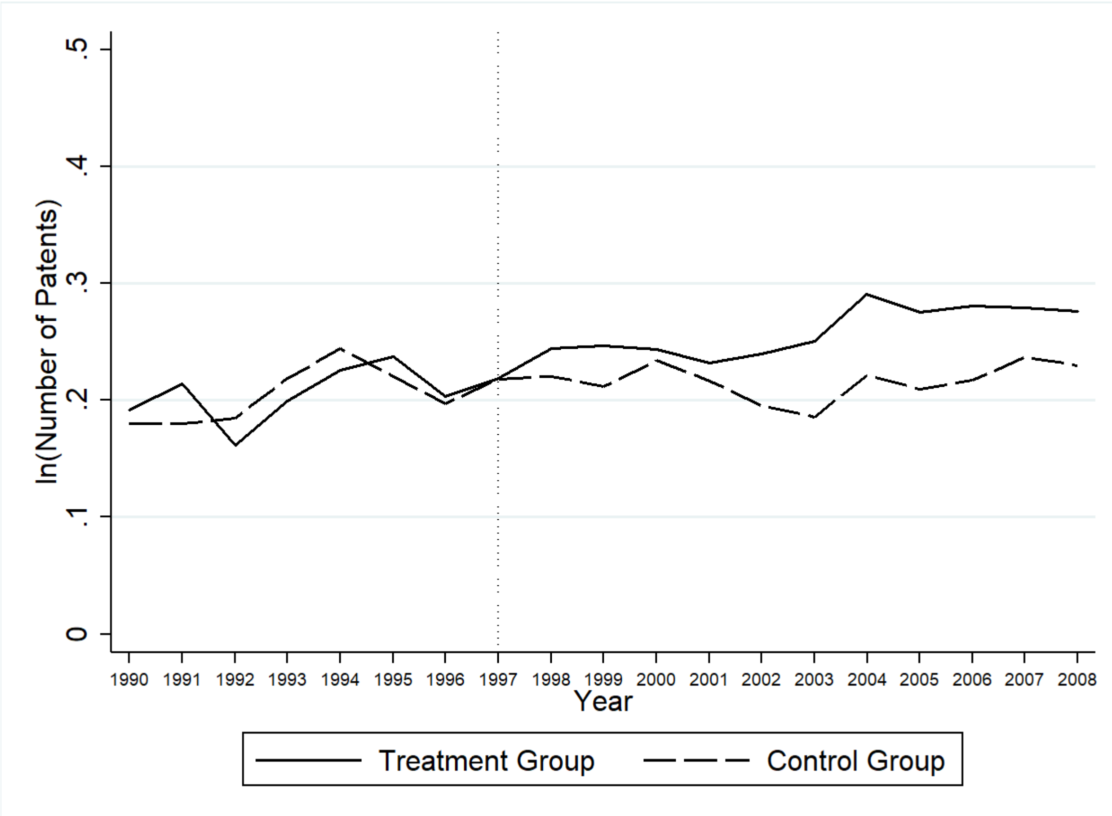
Table A6 Parallel trends assumption first-time applicants – year dummies

		Dependent Variable ln(Number of Patents)
Year		
	1990	Base Group
	1991	-0.0145
		(0.0211)
	1992	0.0019
		(0.0221)
	1993	0.0308
		(0.0258)
	1994	0.0146
		(0.0230)
	1995	0.0016
		(0.0219)
	1996	-0.0135
		(0.0195)
	1997	0.0072
		(0.0235)
Year x TG_j		
	1990	Base Group
	1991	-0.0031
		(0.0272)
	1992	-0.0041
		(0.0275)
	1993	-0.0255
		(0.0307)
	1994	-0.0292
		(0.0279)
	1995	-0.0165
		(0.0276)
	1996	0.0012
		(0.0251)
	1997	-0.0243
		(0.0288)
TG_j		0.0844***
		(0.0238)
Constant		0.0823***
		(0.0177)

AR2	0.0042
R2	0.0055
n	11480
p-Value	0.0029

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Results of the joint F-test for the interaction between the year dummies and the variable TG equals 0.9051 (Prob. > F).

Figure A13 ln(Number of Patents) for treatment and control group in rural areas, before and after the UAS establishment



Source: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version; Control Group curve shifted to the initial level of Treatment Group Curve.

Table A7 Parallel trends assumption rural areas – linear trend

	Dependent Variable ln(Number of Patents)
Year	0.0058
	(0.0038)
Year x TG_j	-0.0019
	(0.0048)
TG_j	-0.0017
	(0.0351)
Constant	0.1854***
	(0.0293)
AR2	-0.0000
R2	0.0004
n	7160
p-Value	0.2645

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A8 Parallel trends assumption rural areas – year dummies

		Dependent Variable ln(Number of Patents)
Year		
	1990	Base Group
	1991	-0.0003
		(0.0213)
	1992	0.0048
		(0.0237)
	1993	0.0383
		(0.0288)
	1994	0.0640**
		(0.0321)
	1995	0.0400
		(0.0276)
	1996	0.0172
		(0.0268)
	1997	0.0378
		(0.0284)
Year x TG_j		
	1990	Base Group
	1991	0.0186
		(0.0298)
	1992	-0.0266
		(0.0315)
	1993	-0.0283
		(0.0354)
	1994	-0.0319
		(0.0387)
	1995	-0.0072
		(0.0362)
	1996	-0.0084
		(0.0355)
	1997	-0.0114
		(0.0371)
TG_j		0.0035
		(0.0389)
Constant		0.1803***

	(0.0317)
AR2	-0.0009
R2	0.0012
n	7160
p-Value	0.2492

Notes: Authors' calculations, based on EPO Worldwide Patent Statistical Database – April 2013 Version. Clustered standard errors on the municipality level are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Result of the joint F-test for the interaction between the year dummies and the variable TG equals 0.8562 (Prob. > F).

Chapter 5

Educational Structures and Risk – The Importance of Type and Field of Education in determining the Variance in Earnings

This chapter was published in 2017 in *Evidence-based HRM: a Global Forum for Empirical Scholarship Vol. 5 Iss. 1* as "The Relative Importance of Type of Education and Subject Area – Empirical Evidence for Educational Decisions", by Pfister, Tuor Sartore, & and Backes-Gellner.

5.1 Introduction

This paper provides evidence based support for educational investments and focuses on the variance of returns rather than the average returns, which have been analyzed extensively in the past. Returns and variance reflect two important aspects of educational investments: profitability and riskiness. In determining variance in earnings, this paper investigates for the first time the relative importance of two factors, the type of education (vocational vs. academic) and the subject area (e.g., commercial or health).

Returns as well as variance differ with respect to two factors. The first factor refers to the type of education and distinguishes between vocational and academic education. The second factor refers to the subject area and distinguishes among fields of education, e.g., commercial, health, STEM (science, technology, engineering and math), and social & service. Studies investigating returns to education show mixed results with respect to type of education. On the one hand, previous research finds that academic education leads to higher earnings returns than vocational education (Conlon, 2005; Dearden, McIntosh, Myck, & Vignoles, 2002; Heijke & Koeslag, 1999). On the other hand, results from countries with stronger vocational educational systems show reasonable—and in some cases even higher—earnings returns to vocational education (Tuor & Backes-Gellner, 2010; Wolter & Weber, 1999). Regarding subject area, results on returns to education are consistent across studies and indicate that the most profitable fields are engineering, health, and business and that the least profitable are education, social sciences, and humanities (Altonji, Blom, & Meghir, 2012; Finnie & Frenette, 2003; Rumberger & Thomas, 1993; Thomas, 2000; Thomas & Zhang, 2005). Only one study, Glocker and Storck (2014), focuses on both factors (type of education and subject area) and finds that university education is not always the most profitable path.[79] Thus, regarding returns to educational investments, previous research shows that both type of education and subject area are related to earnings.

In comparison to returns to education, much less empirical evidence is available regarding the risk associated with human capital investments (Dickson & Harmon, 2011). However, the risk, or more precisely the variance in earnings has recently received considerable attention and is now the focus of an increasing number of studies (e.g., Hartog & Vijverberg, 2007 or Bonin, Dohmen, Falk, Huffman, & Sunde, 2007). Regarding the type of education, Koerselman and Uusitalo (2014) find that, after accounting for returns and risk, university graduates are in a much better position than are vocational high school graduates. Regarding subject area, Christiansen, Joensen, and Nielsen (2007) focus on the risk-return properties of human capital investments and find strong heterogeneity in returns and returns per unit of risk across fields. Thus far, no study reveals the extent to which these two factors contribute to the variance in earnings.

In this paper, we focus on both factors simultaneously and examine the relative importance of type of education and subject area for the variance in earnings. To do so, we decompose the variance in earnings to quantify the separate contribution of each of the two factors to the variance in earnings. Hence, we show the importance of these two factors in determining subsequent earnings.

To quantify the effect of each factor, we proceed in two steps. In the first step, we estimate ordinary least squares (OLS) regressions in the form of Mincer-type earnings equations. Instead of

[79] Glocker and Storck (2014) use the German Micro Census to analyze the earnings risk and returns on investments in 70 fields of education, distinguishing between vocational and academic educations. Their results reveal heterogeneous returns, and in some fields, vocational education is more profitable than academic education. However, do not focus on the variance of these returns.

a continuous variable "years of schooling," we create dummy variables for type of education and subject area. For type of education, we distinguish among purely vocational, purely academic, and mixed education, i.e., individuals who combine vocational and academic educations. For subject area, we form the following five categories: (1) commercial, (2) health, (3) STEM, (4) social & service, and (5) combined subject areas, i.e., individuals who combine different subject areas. In the second step, to analyze the importance of these two educational factors in determining the variance in earnings, we focus on the variance of these returns to type of education and to subject areas and compute the variance decomposition. This variance decomposition allows us to quantify the separate contribution of each educational choice variable to variance in earnings.

To estimate the relative effect of the two educational factors, we use the 2011 Swiss Adult Education Survey (CH-AES 2011) and construct a sample of approximately 1200 individuals, all of whom have a tertiary educational degree. These individuals are all highly educated and therefore constitute a rather homogenous group. The results of the Mincer-type earnings equations show that both type of education and subject area have statistically significant impacts on returns to education. Regarding the type of education, academic and mixed educations yield higher returns than vocational education. Regarding subject area, commercial is the most profitable field, whereas the returns to social & service fields constitute the other side of the spectrum. The results of the variance decomposition show that 9 percent of the explained variance in earnings is attributable to the type of education, whereas nearly 17 percent is attributable to the subject area, that is, subject area explains nearly double the variance in earnings.

Our findings show that earnings variance relates more to subject area than to type of education. Hence, as the decision between vocational and academic education is less relevant than the choice of a specific field, policy discussions on the educational system should devote at least as much attention to the choice of subject area as to the type of education. In addition, given the favorable returns observed for mixed educational careers, the permeability of educational systems should also be discussed.

5.2 Literature Review

Numerous studies focus on the profitability of human capital investments. Studies on the effect of type of education on earnings demonstrate the importance of comparing vocational and academic educations and thereby the potential productivity differences resulting from one year of academic education vs. one year of vocational education and training rather than considering years of schooling. Dearden et al. (2002) use different data sources from the United Kingdom and find that, for a given educational level, returns to academic qualifications are higher compared with vocational qualifications. Similar results have been observed by Conlon (2005) for the United Kingdom and by Heijke and Koeslag (1999) for the Netherlands.

However, the results on the effects of vocational and academic educations on earnings are mixed in European countries (Ryan, 2001). Results from countries with stronger vocational education systems show that vocational education is favorable in terms of monetary and non-monetary outcomes and—in some cases—even preferable to academic education. For example, Wolter and Weber (1999) calculate the returns to different types of education in the form of lifetime income in Switzerland, a country with a strong focus on vocational education. They conclude that any type of post-compulsory education is worthwhile. Moreover, they find no significant differences across types of post-compulsory education. Other studies show that vocational education is favorable in terms of monetary and non-monetary outcomes (see, e.g., Geel & Backes-Gellner, 2011; Tuor & Backes-Gellner, 2010). Thus, distinguishing between academic and vocational paths when examining returns to education is clearly important in European educational systems with strong vocational components.

Regarding subject area, the empirical results are more consistent. Rumberger and Thomas (1993) measure the impact of field of education, school quality, and educational performance on earnings in the United States. They find evidence that all types of qualitative factors have an influence. Regarding the field of education, engineering and health yield the highest gains, followed by science and math, and business. The social sciences and humanities, along with education, yield the lowest returns. Similar results are observed by Thomas (2000) and Thomas and Zhang (2005) for the U.S. and by Finnie and Frenette (2003) for Canada. Thomas (2000) analyzes the effect of college quality, academic performance and college major on the initial earnings and debt ratios of U.S. college graduates. Regarding field of education, i.e., college major, the results are identical: engineering and health-related majors yield the highest returns, whereas education and humanities are the least lucrative fields. Thomas and Zhang (2005) measure the impact of college quality and academic major on earnings for a representative cohort receiving a baccalaureate degree in 1993. They find significant variation across different types of tertiary academic degrees, observing the highest returns for business, engineering, and health.

Finnie and Frenette (2003) analyze differences in earnings by field of study for three cohorts of bachelor’s degree holders in Canada. Among other results, they find the highest returns for health and engineering and the lowest returns for the social sciences and humanities; these results are robust to different sets of control variables. Finally, Altonji et al. (2012) present an overview of selected papers on returns to field of study and conclude that estimates are consistent across fields and over time. The results show a high premium for engineering, followed by science and business. Again, the social sciences, humanities and education fields yield relatively low monetary returns.

Studies that focus on risk are less numerous; the few studies focusing on this aspect show that risk is an important aspect of human capital investment (see, e.g., Hartog, 2011). Harmon, Hogan, and Walker (2003) identify two causes of variation in returns to education: heterogeneity and risk. Heterogeneity refers to differing returns to education among individuals due to factors that are known by the individual but are unobservable to the econometrician, while risk refers to factors that are unknown to both the individual and the econometrician. Using UK Labour Force Survey data from 1993 to 2000, Harmon, Hogan, and Walker (2003) estimate the standard deviation of returns among individuals and find high dispersion in returns to education. Regarding changes in mean return and dispersion over time, they do not find a trend. Schweri, Hartog, and Wolter (2011) investigate expected wage risk directly measuring Swiss students’ anticipated wage distributions and find evidence for a positive association between risk and expected median wage, i.e., evidence for a trade-off between risk and return.

Two studies focus on the factors of type of education and subject area. The first study by Koerselman and Uusitalo (2014) focuses on the returns to and risk of human capital investments. Based on a 22-year panel obtained from Finnish register data, they calculate the mean, variance and skew of lifetime income for different educational levels and thereby distinguish between vocational and academic education. The results show that mean discounted lifetime earnings are much higher for university graduates than for vocational high school graduates. In addition, adjusting for variance and skew, i.e., accounting for risk, does not change the results.

The second study by Christiansen et al. (2007) argue that educational careers differ in terms of both returns and risk. As individuals have heterogeneous utilities regarding the risk of and returns to education, both the mean and the variance of a specific human capital investment influence their educational decisions. These authors therefore focus on the risk-return properties of human capital investments and find strong heterogeneity in returns and returns per unit of risk across fields. Although they focus on both the type and field of education, their study does not provide evidence on these two factors at the same level. For example, they compare an upper-secondary vocational education (Bank Office Clerk Apprenticeship) with a tertiary academic education (Master of Science in Economics). Their comparison of fields at the same level, a strategy to reduce potential ability bias, focuses only on individuals with a tertiary academic educational degree and excludes vocational education.

In sum, both the type of education and the subject area are important in determining the profitability and risk of human capital investments. Therefore, analyses focusing on the effect of education on earnings and on risk must account for the individual's entire educational career. In this study, we therefore focus on the individual's complete educational career and analyze the extent to which subsequent earnings vary with respect the two factors. We expect that subsequent earnings vary less with respect to type of education, as all individuals with a tertiary degree have acquired a substantial amount of human capital and are highly skilled workers, irrespective of whether they followed the academic or the vocational track. However, we expect that subsequent earnings vary more with respect to subject area, as the demand for and the returns to different fields vary in the labor market.

5.3 Data, Sample and Variables

To calculate the contributions of the two factors, type of education and subject area, to variance in earnings, we are interested in analyzing a country that offers vocational and academic education at the upper-secondary and tertiary levels and that provides detailed data on both the type of education and the subject area. The CH-AES 2011 is especially appropriate for our purposes. This survey is part of the Swiss Federal population census, which is completed by computer-assisted telephone interviewing. The CH-AES 2011 contains data on the labor market status, socioeconomic background, and formal and non-formal education of 13,000 individuals. The CH-AES 2011 covers the individual’s entire educational career. Moreover, it makes available detailed descriptions of the type and field of all educational choices that an individual has made, so the survey is particularly appropriate for our study. To improve understanding of our variables, we first describe the Swiss educational system in which academic and vocational educations coexist at the upper-secondary and tertiary levels.[80]

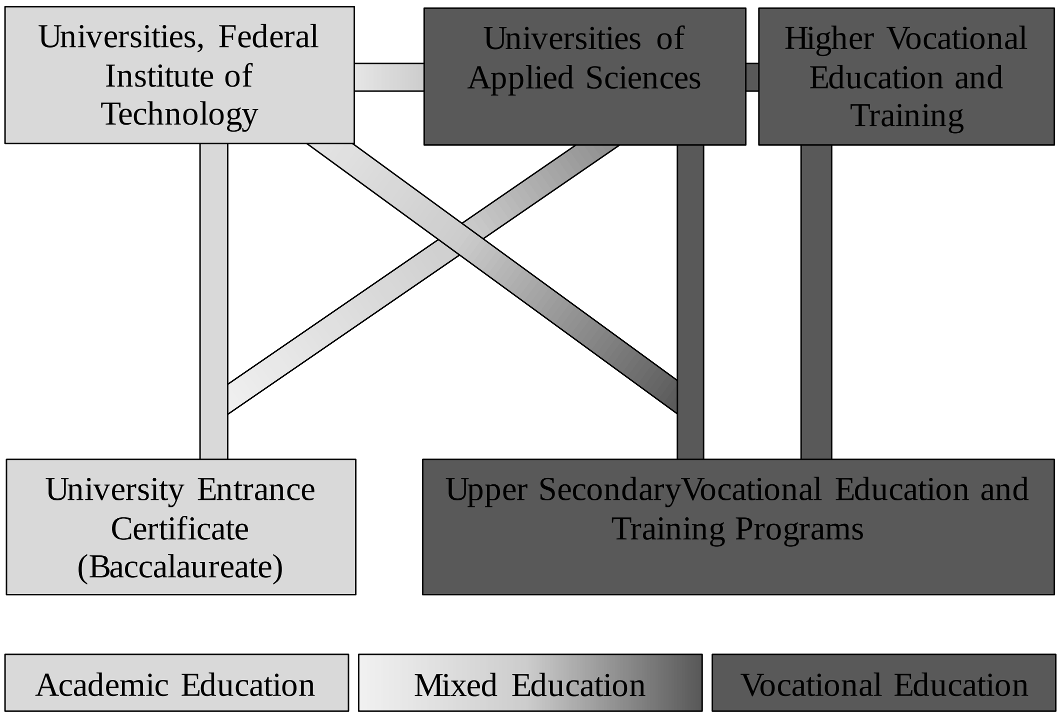
5.3.1 The Swiss Educational System

Figure 7 presents the Swiss educational system and shows that the system provides vocational and academic educations at the upper-secondary and tertiary levels. The system allows for permeability between and within the two levels.[81] A detailed description of the Swiss educational system can be found in the Appendix.

[80] All information regarding the Swiss educational system comes from Swiss Coordination Centre for Research in Education (SCCRE) (2007), SCCRE (2010), SCCRE (2014), and Federal Office for Professional Education and Technology (OPET) (2009).

[81] Universities of Teacher Education and upper-secondary specialized schools are not included in the illustration, as these institutions are not relevant to our analysis.

Figure 7 The Swiss education system



Source: Own illustration, based on Swiss Coordination Centre for Research in Education (SCCRE) (2007, 2010, 2014).

After nine years of compulsory schooling, students aged approximately 15 or 16 choose between vocational and academic upper-secondary educations. Approximately 60 percent of all Swiss students choose an upper-secondary vocational education and training (VET) program (SCCRE 2010, p. 112). These programs combine on-the-job training in the form of a paid apprenticeship in a host company with theoretical instruction at school. Graduates receive an "Advanced Federal Certificate" and continue working as skilled workers within their respective occupational fields; they are employed by either the training company or a new one.

Individuals with upper-secondary vocational degrees have several options for tertiary education. On the one hand, they can continue to follow the vocational track because the Swiss educational system offers a variety of opportunities with different objectives. These opportunities comprise, among others, universities of applied sciences and higher vocational education and training institutions.[82] On the other hand, individuals with upper-secondary vocational degrees can change to the academic tertiary education track (i.e., universities or federal institutes of technology) if they fulfill certain requirements.

In contrast to other Western countries, only approximately 20 percent of Swiss students completing compulsory schooling actually choose the academic track, i.e., obtain a University Entrance Certificate (baccalaureate) (SCCRE 2010, p. 17). This baccalaureate allows its holder unrestricted access to all tertiary academic institutions in Switzerland, i.e., universities and federal institutes of technology. Moreover, if they complete a traineeship in their intended field of study, individuals with a baccalaureate degree also have access to universities of applied science.

5.3.2 Explanatory and Dependent Variables

To measure the contributions of type of education and subject area to variance in earnings, we create two explanatory variables as follows. For the type of education variable, we distinguish among purely academic (light gray in Figure 7), purely vocational (dark gray), and mixed (light and dark gray) educational careers. Purely academic educational paths exclusively include academic components, i.e., baccalaureate, university, or federal institute of technology studies. Purely vocational educational paths exclusively include vocational components, i.e., any type of VET program, studies at a university of applied sciences, or a degree from a higher VET institution.

Mixed educational paths include both academic and vocational components.[83] On the one hand, mixed careers can begin either in an upper-secondary academic institution and end in a tertiary

[82] Following the Federal Act on Funding and Coordination of the Swiss Higher Education Sector (HFKG) of September 30, 2011, the Swiss Confederation fosters a higher education sector comprising different but equivalent types of higher education institutions. These are conventional universities and federal institutes of technology, universities of teacher education, and universities of applied sciences. The HFKG states that these universities of applied sciences provide practical studies and applied research and development. Studying at a university of applied science allows students to perform activities in specific professions requiring the use of research findings and methods. Graduates obtain a qualification that enables them to work in a given profession. For further information, see SCCRE (2014) and Hoeckel, Field, Justesen, & Kim (2009).

[83] Regarding the type of education factor, we include the category for mixed education types because previous research shows that combining vocational and academic education might lead to superior outcomes (e.g., Kang & Bishop, 1989; Bishop & Mane, 2004; Tuor & Backes-Gellner, 2010). In addition, regarding the subject area factor, we include the category for combined subject areas because previous research shows that combining fields might lead to differing outcomes (e.g., Del Rossi & Hersch, 2008; Hemelt, 2010).

vocational institution, e.g., a baccalaureate plus a traineeship plus studies at a university of applied sciences. On the other hand, such careers can begin in an upper-secondary vocational institution and end in a tertiary academic institution, e.g., a VET program plus, having fulfilled the special requirements, studies at a university. Theoretically, numerous combinations of mixed careers are possible. However, we focus on the most common combinations and include only individuals who switch only once between vocational and academic education.

For the subject area variable, we follow the literature (see, e.g., Altonji et al., 2012, Finnie & Frenette, 2003, or Rumberger & Thomas, 1993, for a literature overview of different classifications) and distinguish among five groups. We create dummy variables for commercial, health, STEM, and social & service areas of study. Finally, we create a fifth group for individuals who combine subject areas, combined subject areas.[84]

Our dependent variable, ln(earnings), is the logarithm of annual gross income from earnings. For individuals who work part-time, we calculate the equivalent full-time earnings. In addition, to control for potential part-time effects, we include a part-time dummy (Part-time).

Finally, in addition to experience[85], we include the following set of control variables[86] in our estimation: a dummy for being male (Men), a dummy for being self-employed, dummies for linguistic region (French, Italian and German, with German as the reference group), and for being foreign (Foreign), i.e., not a Swiss citizen.[87]

[84] Table A9 shows further information regarding the classification of subject areas.

[85] The CH-AES 2011 provides no information on experience or experience squared. We therefore use the number of years since the last completed level of education as a proxy. To measure the share of variance in earnings explained by experience, we create seven dummies: The first dummy comprises individuals with labor market experience of 0 to 2 years; the second of 3 to 5; the third of 6 to 8; the fourth of 9 to 13; the fifth of 14 to 18; the sixth of 19 to 25; and the seventh of 26 and more years.

[86] Pereira and Martins (2004) emphasize that the inclusion of covariates related to education leads to a decrease in the coefficient of education, i.e., to biased returns to education. We therefore include only control variables that are assumed independent of educational choice.

[87] These control variables refer to factors that imply differences in earnings. For differences in earnings between women and men, see, e.g., Janssen, Tuor Sartore, and Backes-Gellner (2016); for differences between self-employed and employed individuals, see, e.g., Backes-Gellner and Moog (2013), Backes-Gellner, Tuor, and Wettstein (2010), or Tuor and Backes-Gellner (2010); for differences by linguistic region, see, e.g., Eugster, Lalive, Steinhauer, and Zweimüller (2011).

5.3.3 Sample

Our sample consists of employed individuals between 25 and 65 years old who have completed any type of tertiary education.[88] As these individuals are all highly educated, the sample allows comparing return and risk patterns of a rather homogenous group. Differences therefore refer to the factors type of education and subject area, and not to the level of education, i.e., whether the individual has a longer or a shorter educational career. This subsample represents a large group of the Swiss population; following the Federal Statistical Office, 40 percent of the population living in Switzerland and of age 25 to 64 has a tertiary level educational degree.[89]

We exclude all individuals whose educations are not attributable to vocational or to academic education (such as teachers). Furthermore, we exclude all individuals who switched more than once between the vocational and academic educational tracks, as they are very rare and special cases. In addition, we exclude individuals in the armed forces. Finally, following Gerfin, Leu, and Nyffeler (2003), we drop the highest and the lowest percentile of the earnings distribution. We thus focus on a quite homogeneous sample, as all individuals holding a tertiary educational degree have acquired a substantial amount of human capital and are highly skilled workers. Our final sample contains 1161 individuals.[90]

The descriptive statistics in Table 1 show a mean of ln(earnings) of 11.5058, corresponding to an annual income of approximately 100,000 CHF. These statistics show that 34 percent of the individuals in our sample follow the purely vocational track, approximately 43 percent have a purely academic educational career, and approximately 23 percent have a mixed educational career. Regarding subject area, commercial and STEM fields contain the largest number of individuals: commercial contains 33 percent and STEM 26 percent. The health and combined subject areas both contain approximately 16 percent of all individuals with a tertiary-level degree. The smallest group, at 9 percent, is social & service.

[88] The lower bound of the age restriction implies that individuals most likely have completed their educations. The upper bound of the age restriction implies that individuals who are retired, i.e., individuals older than 65, are excluded.

[89] The information is available from the Swiss Federal Statistical Office, accessed at https://www.bfs.admin.ch/bfs/de/home/statistiken/arbeit-erwerb/erwerbstaetigkeit-arbeitszeit/erwerbspersonen/bildungsstand.html (retrieved January 2019).

[90] Nearly 60% of the 13,000 individuals are employed and provide information regarding their earnings. Of these individuals, 35% have a tertiary educational degree.

Table 25 Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
ln(earnings)	1161	11.5058	0.4938	9.741	13.082
Type of Education					
Vocational	1161	0.3351	0.4722	0	1
Academic	1161	0.4332	0.4957	0	1
Mixed	1161	0.2317	0.4221	0	1
Subject Area					
Commercial	1161	0.3282	0.4697	0	1
Health	1161	0.1628	0.3693	0	1
STEM	1161	0.2618	0.4398	0	1
Social & Service	1161	0.0930	0.2906	0	1
Combined Subject Areas	1161	0.1542	0.3613	0	1
Covariates					
Men	1161	0.5090	0.5001	0	1
German	1161	0.5736	0.4948	0	1
French	1161	0.3635	0.4812	0	1
Italian	1161	0.0629	0.2428	0	1
Self Employed	1161	0.0999	0.3000	0	1
Foreign	1161	0.2377	0.4259	0	1
Part-time	1161	0.3333	0.4716	0	1
Exp: 0-2	1161	0.1309	0.3375	0	1
Exp: 3-5	1161	0.1413	0.3484	0	1
Exp: 6-8	1161	0.1602	0.3670	0	1
Exp: 9-13	1161	0.1559	0.3629	0	1
Exp: 14-18	1161	0.1344	0.3412	0	1
Exp: 19-25	1161	0.1344	0.3412	0	1
Exp: 26 +	1161	0.1430	0.3502	0	1

Source: Own calculations, based on CH-AES 2011.

5.4 Estimation Strategy

To quantify the contributions of type of education and subject area to variance in earnings, we proceed in two steps. In the first step, we estimate OLS regressions in the form of Mincer-type earnings equations, including variables for schooling, experience and experience squared. However, instead of the continuous variable years of schooling, we use dummies that represent our two factors, type of education and subject area. The basic estimation equation is the following:

Equation 7 $$\ln(earnings) = T'\alpha + S'\beta + CV'\gamma + \varepsilon,$$

where *T* refers to type of education and *S* to subject area. For type, we distinguish among purely vocational, purely academic and mixed educations, i.e., individuals who combine vocational and academic educations. For subject area, we distinguish among our five categories: (1) commercial, (2) health, (3) STEM, (4) social & service, and (5) combined subject areas. Finally, we include our set of control variables.

In the second step, we compute the variances of the dependent variable, ln(earnings), of the coefficients of the two independent variables of interest, type of education and subject area, and of the coefficients of our set of control variables.[91] Using Equation 7, the variance of observed ln(earnings) can be decomposed as follows:

[91] We replace each term in Equation 8 with the respective sample analogue to obtain a feasible version of the decomposition. For the variance of ln(earnings), we calculate:

$$s_{yy} = \frac{1}{n-1}\sum(y_i - \bar{y})^2, \text{ where } \bar{y} = \frac{1}{n}\sum y_i.$$

For the variance of the coefficients of type of education and subject area, we calculate:

$$s_{TT} = \frac{1}{n-1}\sum(\mathrm{T}\hat{\alpha}_i - \mathrm{T}\hat{\bar{\alpha}})^2$$

$$s_{FF} = \frac{1}{n-1}\sum(\mathrm{S}\hat{\beta}_i - \mathrm{S}\hat{\bar{\beta}})^2.$$

Finally, for the covariance between type of education and subject area, we calculate:

$$s_{TF} = \frac{1}{n-1}\sum(\mathrm{T}\hat{\alpha}_i - \mathrm{T}\hat{\bar{\alpha}})(\mathrm{S}\hat{\beta}_i - \mathrm{S}\hat{\bar{\beta}}).$$

Equation 8
$$Var(\ln(earnings)) = Var(T\hat{\alpha}) + Var\left(S\hat{\beta}\right) + Var(CV\hat{\gamma})$$
$$+2Cov\left(T\hat{\alpha}, S\hat{\beta}\right) + 2Cov(T\hat{\alpha}, CV\hat{\gamma}) + 2Cov\left(S\hat{\beta}, CV\hat{\gamma}\right) + Var(\hat{\varepsilon}).$$

We then report the ratio of variance in earnings explained by the type of education variable and that explained by the subject area variable: First, we calculate the sum of the variance in ln(earnings) explained by type of education, subject area, experience and control variables. Second, we divide the respective variance and covariance components by this sum of explained variance. This variance decomposition allows us to quantify the separate contributions of type of education and subject area to variance in earnings.[92]

[92] Studies investigating risk-return properties considered—in addition to the variance of the distribution—the kurtosis, a measure that informs whether individuals more likely attain the upper part (skewed to the left) or the lower part (skewed to the right) of the distribution (see, e.g., Koerselman and Uusitalo, 2014). However, the number of observations is too small in CH-AES 2011 to consider this measure.

5.5 Results

The first step in quantifying the impact of type of education and subject area on variance in earnings implies the use of Mincer-type earnings equations. Table 26 reports the results of the earnings equation (Equation 7). Specifications (1) and (2) represent separate regressions of the dummies for type of education and experience on ln(earnings) and the dummies for subject area and experience, respectively. Specification (3) comprises dummies for both factors, as well as experience, and indicates that results for the type of education factor are robust to the inclusion of the subject area factor.[93]

In addition to all educational choice variables, specification (4) includes our set of control variables for being male, linguistic region, self-employment, foreign nationality and working part-time. Regarding type of education, the results indicate higher returns for academic and mixed educations. Both are statistically significant at the one-percent level. The difference between them is statistically insignificant. Regarding subject area, individuals in the STEM fields earn 8.8 percent less and individuals in the social & service fields 30.0 percent less than do individuals in the commercial fields; these differences are significant. However, the health and mixed fields show no significant differences in returns compared with the commercial fields. Finally, the results regarding experience and control variables are in line with previous research.

[93] Specification 3 shows that the returns for purely academic and mixed educational careers slightly increase after the inclusion of the factor subject area. The reason might be that these individuals having a purely academic or a mixed educational career are more likely in the low-paying subject areas STEM and Social & Service.

Table 26 Mincer-type earnings regressions

	ln(earnings)			
	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Vocational	Base Group		Base Group	Base Group
Academic	0.0703**		0.1122***	0.1437***
	(0.0324)		(0.0345)	(0.0344)
Mixed	0.0483		0.0759**	0.1062***
	(0.0381)		(0.0380)	(0.0375)
Commercial		Base Group	Base Group	Base Group
Health		-0.0890**	-0.1047**	-0.0245
		(0.0421)	(0.0422)	(0.0421)
STEM		-0.0402	-0.0625*	-0.0883**
		(0.0365)	(0.0371)	(0.0364)
Social & Service		-0.3221***	-0.3512***	-0.3001***
		(0.0515)	(0.0521)	(0.0511)
Combined Subject Areas		-0.0769*	-0.0459	-0.0227
		(0.0429)	(0.0438)	(0.0424)
Experience	Included	Included	Included	Included
Control Variables				Included
Constant	11.2239***	11.3468***	11.2890***	11.2411***
	(0.0434)	(0.0437)	(0.0473)	(0.0495)
Adjusted R-squared	0.0636	0.0902	0.0971	0.1631
R-squared	0.0700	0.0981	0.1064	0.1761
N	1161	1161	1161	1161
Prob>F	0.000	0.000	0.000	0.000

Source: Own calculations, based on CH-AES 2011; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level. Table A10 shows the results for experience and all control variables.

The second step in quantifying the effect of type of education and subject area on variance in earnings is a variance decomposition regarding the two factors. We calculate the extent to which type of education and subject area contribute to total variance in ln(earnings). The first column of Table 27 follows Equation 8 and reports the variance in ln(earnings) explained by the respective variance and covariance components. The second column reports these components' relative shares of variance in ln(earnings) explained by the model. We calculate these shares by dividing the respective variance or covariance component by the sum of the variance explained by our model.

The first two rows of Table 27 shows that the variance of ln(earnings) is approximately 0.2438. Our explanatory variables explain 17.61 percent of the variance in ln(earnings), implying that our model has an R-squared of .1761.

The third row depicts the variance in the three dummies for type of education, vocational, academic and mixed, and the fourth row reports the five dummies for subject area, commercial, health, STEM, social & service, and mixed fields. The variance for type of education is 0.0040, and the share of the explained variance in ln(earnings) approximately 9 percent. The variance for subject area equals 0.0072, and the respective share of the explained variance in ln(earnings) approximately 17 percent. The covariance between type and field of education equals -0.0023 and accounts for approximately 5 percent of the explained variance.

Rows five through ten report the variances and relative shares of experience and our set of control variables. The results for the dummies for experience and the dummy for gender are the largest: The variance equals 0.0140 for experience and 0.0102 for gender. Approximately 33 percent of the variance in ln(earnings) is attributable to experience, and approximately 24 percent is attributable to gender. The shares of linguistic region, self-employment, being foreign and working part-time explained between 3 percent and 5 percent of variation in earnings.

In summary, the subject area factor accounts for nearly twice the explained variance in earnings as that attributable to the type of education factor.

Table 27 Variance decomposition

	Variance	Share of total Variance	Share of explained Variance
Total Variance of ln(Earnings)	0.2438	100%	
Explained Variance of ln(Earnings)	0.0429	17.61%	100%
Components of Variance:			
Type of Education	0.0040	1.65%	9.36%
Subject Area	0.0072	2.94%	16.72%
Gender (Male)	0.0102	4.20%	23.86%
Linguistic Region	0.0019	0.79%	4.48%
Self-Employed	0.0002	0.07%	0.37%
Foreign	0.0017	0.71%	4.04%
Part-Time	0.0014	0.57%	3.22%
Experience	0.0140	5.75%	32.68%

Source: Own calculations, based on CH-AES 2011. Table A11 shows the results for the respective covariance.

5.6 Subsample Analysis

In the next step, we focus on two important aspects. First, we consider subsamples for women and for men to determine whether the results differ with respect to gender. Second, to account for differences among subgroups constructed on the basis of the two factors, we calculate the explained variance in earnings attributable to subject area within each type of education and the explained variance in earnings attributable to type of education within each subject area.

5.6.1 Gender

The literature indicates that returns to education differ between women and men (see, e.g., Harmon, Oosterbeek, and Walker, 2003). We therefore estimate returns to type of education and subject area for subsamples of women and men. Table A12 and Table A13 report the results of the earnings equations for women and men. The results from the earnings equations are similar for women and men. However, women appear to exhibit greater variance in returns to type of education, whereas men appear to exhibit greater variance in returns to field of education.

The results of the variance decomposition confirm these differences. Table 28 shows that variance in earnings is nearly identical between women and men. The decomposition results for women show that the variance in both type of education and subject area equals 0.057. Hence, both type of education and subject area explain approximately 22 percent of the variance in earnings. In contrast, the decomposition results for men show a lower variance for type of education (0.0033) and a much higher variance for subject area (0.0188). Hence, less than 10 percent of the explained variance in earnings is attributable to type of education, whereas more than 35 percent of the explained variance in earnings is associated with subject area.

Consequently, the two factors differ between women and men. Whereas for women, both factors are equally important, for men, subject area is associated with considerably more variance in earnings than is type of education.[94]

[94] The question of how differences in the joint distribution of education type and subject area are related to gender differences has to be answered by future research, as the number of cases in the cells is too small for further analyses.

Table 28 Variance decomposition for women and men

	Women			Men		
	Variance	Share of total Variance	Share of explained Variance	Variance	Share of total Variance	Share of explained Variance
Total Variance of ln(Earnings)	0.2277	100%		0.2258	100%	
Explained Variance of ln(Earnings)	0.0252	11.07%	100%	0.0334	14.78%	100%
Components of Variance:						
Type of Education	0.0057	2.49%	22.46%	0.0033	1.45%	9.83%
Subject Area	0.0057	2.50%	22.56%	0.0118	5.21%	35.22%
Linguistic Region	0.0033	1.47%	13.25%	0.0017	0.77%	5.24%
Self-Employed	0.0003	0.14%	1.22%	0.0000	0.02%	0.10%
Foreign	0.0010	0.44%	3.95%	0.0023	1.01%	6.81%
Part-Time	0.0010	0.44%	3.95%	0.0007	0.33%	2.22%
Experience	0.0132	5.81%	52.48%	0.0168	7.44%	50.33%

Source: Own calculations, based on CH-AES 2011. Table A14 Table A15 show the results for the respective covariance.

The share of variance explained by linguistic region highly differs between women and men. One reason that women's earnings vary more with the linguistic region than men's earnings could be discriminatory social attitudes (see Janssen et al., 2016).

5.6.2 Type of Education and Subject Area

Our baseline model does not account for interaction effects. In a last step, we therefore focus on differences among the subgroups constructed on the basis of the two factors: type of education and subject area.

First, we report the extent to which the subject area factor contributes to variance in earnings within each type of education. We estimate Mincer-type earnings regressions on subsamples of individuals with purely vocational educations, of individuals with purely academic educations, and of individuals with mixed educations. We then decompose the variance regarding subject area, experience, and our set of control variables and calculate the share of variance explained by the subject area factor.

Table A16 reports the results for the subject area factor within each type of education. The overall result of our baseline model remains unchanged: Returns are largest for the commercial fields and lowest for social & service fields.[95]

Table 29 reports the respective variance decomposition within the three subsamples. The first two rows show that the variance in ln(earnings) is lowest for individuals with purely vocational educations and highest for individuals whose educations are purely academic. Hence, individuals following a purely academic career face more variance in subsequent earnings than do individuals following a purely vocational career. The subject area factor has a variance of 0.0079 in the vocational subsample and of 0.0071 in the academic subsample. The share of explained variance equals 17 percent for individuals with purely vocational educations and 11 percent for individuals with purely academic educations. For individuals combining vocational and academic educations, the variance of the subject area factor equals 0.016 and is considerably higher than the variance of individuals focusing on one type of education. Similarly, the share of explained variance in earnings attributable to subject area is more than 30 percent.

[95] Results in Table A16 do not point towards complementarities for individuals who just combine different types of education or who just combine different subject areas. However, further break downs of the cells suggest that those individuals who change their subject when they mix their type of education (like for example coming from a mechanical vocational training and then moving into an academic management education) might gain from complementarity effects. However, as cells become rather small with these breakdowns, further research is needed.

Table 29 Variance decomposition within each type of education

	Vocational			Academic			Mixed		
	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.
Total Variance of ln(Earnings)	0.1943	100%		0.2911	100%		0.2239	100%	
Explained Variance of ln(Earnings)	0.0461	24%	100%	0.0628	21.55%	100%	0.0497	22.21%	100%
Components of Variance:									
Subject Area	0.0079	4.08%	17.19%	0.0071	2.45%	11.36%	0.0155	6.94%	31.27%
Gender (Male)	0.0196	10.06%	42.46%	0.0048	1.65%	7.66%	0.0070	3.11%	14.00%
Linguistic Region	0.0008	0.44%	1.84%	0.0026	0.90%	4.17%	0.0047	2.10%	9.43%
Self-Employed	0.0087	4.47%	18.87%	0.0013	0.45%	2.09%	0.0001	0.03%	0.14%
Foreign	0.0001	0.08%	0.32%	0.0021	0.73%	3.37%	0.0020	0.88%	3.97%
Part-Time	0.0001	0.05%	0.21%	0.0058	2.00%	9.27%	0.0001	0.04%	0.18%
Experience	0.0046	2.35%	9.92%	0.0265	9.09%	42.16%	0.0172	7.69%	34.61%

Source: Own calculations, based on CH-AES 2011. Table A17 shows the results for the respective covariance.

Second, we analyze the extent to which the type of education factor contributes to the variance in earnings within each subject area. We estimate earnings regressions on subsamples of individuals with degrees in the commercial, health, STEM, and social & service fields and individuals with degrees in more than one subject area, that is, the combined subject areas category. We then perform a variance decomposition regarding type of education, experience and our control variables to identify the relative contribution of each component to the explained variance in earnings.

Table A18 reports the results for the type of education factor within each subject area. The overall result of the baseline model remains unchanged: Academic and mixed educations yield higher returns than vocational educations. However, for individuals who completed their educations within the commercial fields, the type of education is irrelevant.

Table 29 reports the variance decomposition for each of the five subsamples. The first two rows comprise the variance in ln(earnings) within each subsample and shows that, at values between

0.20 and 0.24, they are lowest within the commercial, STEM and combined subject areas subsamples. The variance in earnings within the health and social & service subsamples are considerably higher, with values of 0.28 and 0.31, respectively.

The third row reports the variance of the type of education factor within each subsample as well as its share of explained variance in earnings. Within the commercial subsample, the type of education factor exhibits a variance of 0.00003, implying that it explains 0.1 percent of variance in earnings. Within STEM and social & services fields, the variance is 0.0045 and 0.0035, respectively, which equals shares of explained variance of 7.7 percent and 5.3 percent. Within the health and mixed field subsamples, the variance of the type of education is much higher and equals 0.011 and 0.023. The respective share of explained variance in earnings of type of education is 16.5 percent within the health subsample and 36.3 percent within the mixed fields subsample.

In summary, the subsample analyses show that the main results of our baseline model remain unchanged. The subsample analysis for gender shows that for women, both factors are equally important in terms of variance in earnings. For men, the variance in earnings attributable to the subject area factor is three to four times larger than the variance attributable to type of education.

The subsample analyses that consider the effect of each factor on subgroups constructed based on the other factor reveal relatively high shares of explained variance attributable to subject area within the type of education subsamples. Within the sample of individuals combining vocational and academic education, subject area explains the largest share of variance in earnings.

Within subject area subsamples, the shares of explained variance in earnings attributable to type of education are relatively low. However, there are two exceptions: The first refers to the health subsample in which type of education explains a higher share of variance in earnings. The second refers to individuals combining different subject areas whose earnings vary considerably more with the type of education in which they choose to specialize. These results might indicate complementarities in combinations of different types of education and different subject areas.

Table 30 Variance decomposition within each subject area

	Commercial			Health			STEM			Social & Service			Combined Subject Areas		
	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.	Variance	Share of total Var.	Share of explained Var.
Total Var. of ln(Earnings)	0.2000	100%		0.2826	100%		0.2432	100%		0.3101	100%		0.2055	100%	
Explained Var. of ln(Earnings)	0.0308	15.43%	100%	0.0694	24.56%	100%	0.0589	24.20%	100%	0.0671	21.66%	100%	0.0632	30.77%	100%
Components of Var.:															
Type of Education	0.0000	0.02%	0.10%	0.0114	4.05%	16.49%	0.0045	1.87%	7.73%	0.0035	1.14%	5.28%	0.0229	11.17%	36.30%
Gender (Male)	0.0063	3.14%	20.33%	0.0086	3.05%	12.41%	0.0106	4.36%	18.03%	0.0029	0.94%	4.34%	0.0158	7.69%	24.99%
Linguistic Region	0.0004	0.21%	1.36%	0.0108	3.81%	15.52%	0.0018	0.76%	3.13%	0.0011	0.37%	1.70%	0.0054	2.64%	8.58%
Self-Employed	0.0021	1.05%	6.83%	0.0064	2.28%	9.28%	0.0020	0.84%	3.48%	0.0217	7.00%	32.32%	0.0060	2.90%	9.42%
Foreign	0.0020	1.00%	6.49%	0.0000	0.01%	0.04%	0.0015	0.62%	2.55%	0.0012	0.40%	1.85%	0.0002	0.09%	0.31%
Part-Time	0.0064	3.19%	20.70%	0.0000	0.01%	0.02%	0.0012	0.51%	2.10%	0.0014	0.45%	2.08%	0.0006	0.30%	0.97%
Exp.	0.0094	4.70%	30.48%	0.0135	4.79%	19.49%	0.0350	14.40%	59.51%	0.0536	17.29%	79.82%	0.0122	5.92%	19.23%

Source: Own calculations, based on CH-AES 2011. Table A19 shows the results for the respective covariance

5.7 Conclusion

This study is the first to demonstrate the relative importance of type of education in comparison to subject area in determining variance in earnings for highly educated individuals, i.e., individuals having a tertiary educational degree. The results show that subject area explains nearly twice the variance in earnings as that explained by type of education. Within the subsamples for type of education and subject area, the results essentially remain unchanged. One possible explanation for why earnings vary more for subject area than for type of education is that the market value of tasks varies more by subject areas than by type of education. Altonji *et al.* (2012) argue that the value of different tasks in the labor market varies considerably. As these tasks relate to specific skills and knowledge developed in different educational careers, the returns to education vary. Another explanation is that differences in the demand for different types of education are less pronounced than differences in the demand for different fields, i.e., the labor market demand for academic and for vocational qualifications differs only marginally. Future research might assess the validity of these different explanations and explicitly consider potential biases due to ability sorting or self-selection into specific subject areas or types of education.

Our analysis is of high policy relevance. As our empirical evidence shows that variance in earnings—and thereby risk—relate more to subject area than to type of education, an evidence based decision of individuals caring about the risk of their educational decision should care more about the selection of a specific subject area than the choice between vocational and academic educational tracks (which caught most of the attention in the past). Educational decisions as part of HRM policies should also devote as much attention to the choice of subjects or occupations as to the types of education, i.e., vocational or academic. This is especially important for companies or countries planning to introduce or to extend vocational education as part of their human resources strategies.

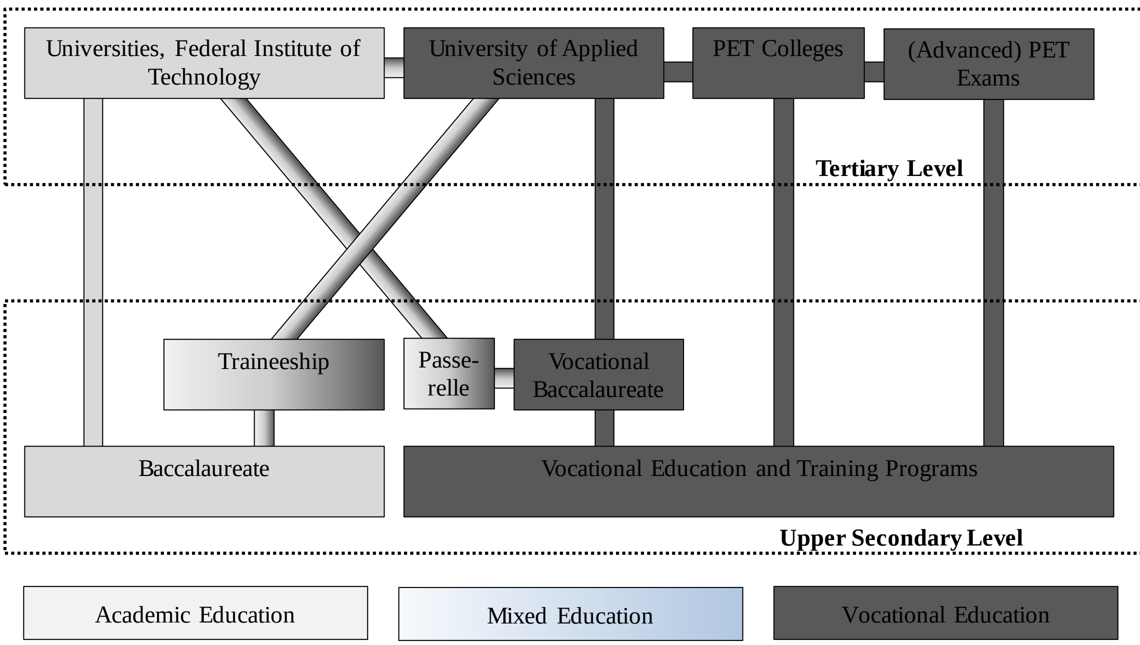
In addition, our results show that a combination of vocational and academic education has high returns as well as low variances. Hence, permeability between the two tracks, i.e., the opportunity to combine academic and vocational educations, appears to be a critical factor, as potential complementarities might exist between different types of education.

Future research might focus on the individuals' decision process and potential endogenous selection into different types or fields of education. While our analysis is less prone to the ability bias, given that our sample includes highly-skilled individuals only, character skills and preferences might determine the choice of a particular type or field of education. For example, studies in the STEM-field, such as electrical engineering, might require a very accurate and meticulous way of working. Individuals being very conscientious might self-select into such a STEM-field, because their character skills they possess allows them to be successful in that field. Higher earnings in such a field thus relate to the higher degree of conscientiousness. Without data on such conscientiousness, i.e., not controlling for self-selection based on particular character skills, the results of our analyses suffer an upward bias. Data including measures for non-cognitive skills, such as conscientiousness, openness to experience, or locus of control, and measures for preferences, e.g., time and risk preferences, thus might be promising to investigate potential endogeneity in the individuals decision for particular educational structures.

5.8 Appendix

After nine years of compulsory schooling, students aged approximately 15 and 16 choose either a vocational or an academic upper-secondary education. Approximately 60 percent of all Swiss students choose a dual-track vocational education and training (VET) program (SCCRE 2010, p. 112). These programs combine on-the-job training, in the form of a paid apprenticeship in a host company, with theoretical teaching at school. Graduates receive an "Advanced Federal Certificate" and continue working as skilled workers within their respective occupational fields, either in the training company or a new one (Tuor & Backes-Gellner, 2010, p. 498).[96]

Figure A14 The Swiss Educational System



Source: Own illustration, based on SCCRE (2007, 2010, 2014).

[96] Beyond these apprenticeships, an additional 10% of students attend full-time VET schools after compulsory education. Less than 5% of all students attend an upper-secondary specialized school (SCCRE, 2010, p. 17). Full-time VET schools do not offer work-based training, a characteristic peculiar to apprenticeship programs. Upper-secondary specialized schools provide both extensive general educations and occupation-specific knowledge to prepare students for further professional education and training at the tertiary vocational level. In addition, upper-secondary specialized schools offer an upper-secondary specialized baccalaureates for specific occupations.

Individuals with an upper-secondary vocational degree have several options for tertiary education. On the one hand, they can continue to follow the vocational track because the Swiss educational system offers a variety of opportunities with different objectives. First, individuals having obtained a federal vocational baccalaureate during or after an upper-secondary VET program have access to universities of applied science. While these universities of applied science and conventional universities are of equal status, their focus in terms of teaching and research differ. Universities of applied science emphasize practically oriented and applied research and development. Therefore, the studies they offer focus on practice, include general vocational training, and prepare their students for occupations that require the application of scientific knowledge and methods.

Second, VET graduates can acquire necessary competencies in demanding occupational activities or activities with high responsibilities through professional education and training (PET) colleges. PET colleges provide nationally approved core curricula that enhance technical and managerial expertise in the student's occupational field. The admission requirements are a VET, federal vocational baccalaureate or baccalaureate degree as well as a certain amount of professional experience and/or a goal score on an aptitude test.

Third, federal professional education and training diploma examinations and advanced federal professional education and training diploma examinations ("Meisterprüfung") constitute another tertiary vocational education option. These examinations assess whether candidates are able to perform demanding management-related or technical activities. Advanced federal professional education and training diploma examinations are more challenging, as they test the candidate's field expertise or his or her ability to independently manage a small- or medium-sized business. Eligibility requirements for the examinations are the equivalent of those of PET colleges. However, in contrast to PET college curricula, the curricula for these examinations are not nationally approved. Only the mode and content of the examinations are federally recognized.

On the other hand, individuals with a VET degree have access to academic tertiary education in combination with a good score on the University Aptitude Test. Approximately 3 percent of the 2006 cohort of upper-secondary students with federal vocational baccalaureate degrees entered a tertiary academic institution in this manner (Federal Statistical Office, 2013, p. 9). In addition, students possessing a bachelor's degree from a university of applied sciences can begin a master's degree program at a conventional academic institution at the tertiary level.

In contrast to other Western countries, only approximately 20 percent of Swiss students completing compulsory schooling choose the academic track, i.e., obtain a baccalaureate (SCCRE 2010, p. 17). This baccalaureate allows its holders unrestricted access to all tertiary academic institutions in Switzerland, i.e., universities and federal institutes of technology. Moreover, if they complete a traineeship in their intended field of study, individuals with a baccalaureate degree also have access to universities of applied sciences.

Figure A14 illustrates the Swiss educational system.[97] It shows that the system provides vocational and academic education at the upper-secondary and tertiary levels and allows for permeability between and within the two levels.

[97] Neither universities of teacher education nor upper-secondary specialized schools are included in the illustration, as these institutions are not relevant to our analysis.

Table A9 Classification of subject areas

Subject Area	ISCO-08 classification
Commercial	1, 24, 261, 2631, 33, 3411, 4, 52
Health	22, 2634, 32, 53
STEM	21, 25, 31, 35
Social & Service	262, 2632, 2633, 2635, 2636, 264, 265, 3412, 3413, 342, 343, 51, 54
Excluded: Manual	6, 7, 81, 82, 83, 9

Source: Own illustration, based on Federal Statistical Office FSO (2003) and International Labour Organization ILO (2008).

Hoeckel et al. (2009) argue that the International Standard Classification of Education (ISCED) is a weak instrument for identifying vocational fields at the secondary and tertiary levels. We thus use the Swiss Standard Classification of Occupations 2000 from FSO (2003) and the ISCO-08 classification from ILO (2008) to identify and create homogeneous groups of subject areas. In addition, the subject area “Manual” comprises tertiary education in a manual labor field, such as foreman or wood engineer. We exclude individuals having tertiary education in these fields, as this subject area exclusively exists within the vocational type of education.

Table A10 Mincer-type earnings regressions

	ln(earnings)			
	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Vocational	Base Group			Base Group
Academic	0.0703**		0.1122***	0.1437***
	(0.0324)		(0.0345)	(0.0344)
Mixed	0.0483		0.0759**	0.1062***
	(0.0381)		(0.0380)	(0.0375)
Commercial		Base Group	Base Group	Base Group
Health		-0.0890**	-0.1047**	-0.0245
		(0.0421)	(0.0422)	(0.0421)
STEM		-0.0402	-0.0625*	-0.0883**
		(0.0365)	(0.0371)	(0.0364)
Social & Service		-0.3221***	-0.3512***	-0.3001***
		(0.0515)	(0.0521)	(0.0511)
Combined Subject Areas		-0.0769*	-0.0459	-0.0227
		(0.0429)	(0.0438)	(0.0424)
Experience: 0-2 years	Base Group	Base Group	Base Group	Base Group
Experience: 3-5 years	0.1026*	0.0820	0.0805	0.0678
	(0.0538)	(0.0532)	(0.0530)	(0.0514)
Experience: 6-8 years	0.2216***	0.2098***	0.2000***	0.1995***
	(0.0523)	(0.0516)	(0.0515)	(0.0500)
Experience: 9-13 years	0.2888***	0.2644***	0.2659***	0.2677***
	(0.0526)	(0.0520)	(0.0518)	(0.0506)
Experience: 14-18 years	0.3556***	0.3455***	0.3460***	0.3286***
	(0.0545)	(0.0538)	(0.0536)	(0.0522)
Experience: 19-25 years	0.3295***	0.3191***	0.3136***	0.2992***
	(0.0545)	(0.0538)	(0.0536)	(0.0523)
Experience: > 26 years	0.3715***	0.3503***	0.3510***	0.3256***
	(0.0537)	(0.0532)	(0.0530)	(0.0521)
Gender (Men)				0.2023***
				(0.0315)
German				Base Group
French				-0.0442
				(0.0290)
Italian				-0.1759***
				(0.0562)
Self-employed				-0.0421
				(0.0451)
Foreign				-0.0977***
				(0.0329)
Parttime				-0.0788**
				(0.0326)
Constant	11.2239***	11.3468***	11.2890***	11.2411***
	(0.0434)	(0.0437)	(0.0473)	(0.0495)
Adjusted R-squared	0.0636	0.0902	0.0971	0.1631
R-squared	0.0700	0.0981	0.1064	0.1761
N	1161	1161	1161	1161
Prob>F	0.000	0.000	0.000	0.000

Source: Own calculations, based on CH-AES 2011; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level

Table A11 Variance decomposition

	Variance	Share of total Variance	Share of Explained Variance
Total Variance of ln(Earnings)	0.2438	100%	
Explained Variance of ln(Earnings)	0.0429	17.61%	100%
Components of Variance:			
Type of Education	0.0040	1.65%	9.36%
Subject Area	0.0072	2.94%	16.72%
Experience	0.0140	5.75%	32.68%
Gender (Male)	0.0102	4.20%	23.86%
Linguistic Region	0.0019	0.79%	4.48%
Self-Employed	0.0002	0.07%	0.37%
Foreign	0.0017	0.71%	4.04%
Part-Time	0.0014	0.57%	3.22%
Components of Covariance			
Cov(Type. Subject Area)	-0.0023	-0.95%	-5.38%
Cov(Type. Gender)	0.0001	0.05%	0.28%
Cov(Type. Linguistic Region)	-0.0007	-0.29%	-1.66%
Cov(Type. Self-Employed)	-0.0001	-0.03%	-0.17%
Cov(Type. Foreign)	-0.0012	-0.48%	-2.70%
Cov(Type. Part-Time)	0.0000	0.01%	0.04%
Cov(Type. Experience)	0.0002	0.10%	0.55%
Cov(Subject Area. Gender)	-0.0004	-0.17%	-0.98%
Cov(Subject Area. Linguistic Region)	0.0008	0.32%	1.84%
Cov(Subject Area. Self-Employed)	0.0001	0.02%	0.14%
Cov(Subject Area. Foreign)	0.0002	0.08%	0.43%
Cov(Subject Area. Part-Time)	0.0006	0.24%	1.38%
Cov(Subject Area. Experience)	0.0001	0.03%	0.20%
Cov(Gender. Linguistic Region)	0.0000	-0.02%	-0.09%
Cov(Gender. Self-Employed)	0.0000	-0.01%	-0.03%
Cov(Gender. Foreign)	0.0001	0.03%	0.20%
Cov(Gender. Part-Time)	0.0034	1.41%	8.00%
Cov(Gender. Experience)	0.0030	1.21%	6.90%
Cov(Linguistic Region. Self-Employed)	0.0000	0.01%	0.06%
Cov(Linguistic Region. Foreign)	0.0001	0.03%	0.14%
Cov(Linguistic Region. Part-Time)	0.0000	0.01%	0.06%
Cov(Linguistic Region. Experience)	-0.0008	-0.34%	-1.93%
Cov(Self-Employed. Foreign)	0.0000	-0.02%	-0.11%
Cov(Self-Employed. Part-Time)	0.0000	0.01%	0.08%
Cov(Self-Employed. Experience)	-0.0004	-0.15%	-0.84%
Cov(Foreign. Part-Time)	-0.0003	-0.13%	-0.74%
Cov(Foreign. Experience)	0.0001	0.03%	0.14%
Cov(Part-Time. Experience)	-0.0002	-0.10%	-0.54%

Source: Own calculations, based on CH-AES 2011.

Table A12 Mincer-type earnings regressions for women

	ln(earnings)			
	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Vocational	Base Group			Base Group
Academic	0.0951**		0.1504***	0.1736***
	(0.0459)		(0.0508)	(0.0520)
Mixed	0.0795		0.1065**	0.1233**
	(0.0513)		(0.0525)	(0.0533)
Commercial		Base Group	Base Group	Base Group
Health		-0.0333	-0.0465	-0.0332
		(0.0520)	(0.0518)	(0.0524)
STEM		-0.1121*	-0.1568**	-0.1474**
		(0.0612)	(0.0629)	(0.0627)
Social & Service		-0.2109***	-0.2479***	-0.2211***
		(0.0681)	(0.0688)	(0.0697)
Combined Subject Areas		-0.0845	-0.0370	-0.0139
		(0.0589)	(0.0606)	(0.0606)
Experience: 0-2 years	Base Group	Base Group	Base Group	Base Group
Experience: 3-5 years	0.0572	0.0468	0.0343	0.0443
	(0.0700)	(0.0701)	(0.0698)	(0.0703)
Experience: 6-8 years	0.2623***	0.2577***	0.2410***	0.2606***
	(0.0665)	(0.0662)	(0.0661)	(0.0667)
Experience: 9-13 years	0.2380***	0.2174***	0.2182***	0.2608***
	(0.0683)	(0.0683)	(0.0678)	(0.0689)
Experience: 14-18 years	0.2712***	0.2652***	0.2539***	0.2773***
	(0.0745)	(0.0742)	(0.0738)	(0.0745)
Experience: 19-25 years	0.2954***	0.2882***	0.2750***	0.2883***
	(0.0732)	(0.0730)	(0.0726)	(0.0731)
Experience: > 26 years	0.2233***	0.2172***	0.2075***	0.2437***
	(0.0748)	(0.0747)	(0.0743)	(0.0752)
German				Base Group
French				-0.0104
				(0.0420)
Italian				-0.2405***
				(0.0815)
Self-employed				-0.0589
				(0.0658)
Foreign				-0.0736
				(0.0483)
Parttime				-0.0634
				(0.0410)
Constant	11.1270***	11.2570***	11.1828***	11.2148***
	(0.0540)	(0.0564)	(0.0616)	(0.0634)
Adjusted R-squared	0.0498	0.0578	0.0695	0.0833
R-squared	0.0632	0.0743	0.0891	0.1107
N	570	570	570	570
Prob>F	0.000	0.000	0.000	0.000

Source: Own calculations, based on CH-AES; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A13 Mincer-type earnings regressions for men

	ln(earnings)			
	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Vocational	Base Group			Base Group
Academic	0.0408		0.0886**	0.1269***
	(0.0432)		(0.0451)	(0.0462)
Mixed	0.0577		0.0745	0.1025*
	(0.0538)		(0.0528)	(0.0538)
Commercial		Base Group	Base Group	Base Group
Health		0.0467	0.0206	0.0216
		(0.0758)	(0.0767)	(0.0780)
STEM		-0.0808*	-0.0951**	-0.0746
		(0.0446)	(0.0452)	(0.0456)
Social & Service		-0.4198***	-0.4446***	-0.4174***
		(0.0744)	(0.0754)	(0.0761)
Combined Subject Areas		-0.0421	-0.0228	-0.0202
		(0.0587)	(0.0599)	(0.0599)
Experience: 0-2 years	Base Group	Base Group	Base Group	Base Group
Experience: 3-5 years	0.0876	0.0818	0.0890	0.0940
	(0.0801)	(0.0780)	(0.0779)	(0.0778)
Experience: 6-8 years	0.1269	0.1220	0.1185	0.1267
	(0.0794)	(0.0774)	(0.0773)	(0.0770)
Experience: 9-13 years	0.2810***	0.2581***	0.2629***	0.2752***
	(0.0784)	(0.0764)	(0.0764)	(0.0769)
Experience: 14-18 years	0.3387***	0.3552***	0.3642***	0.3724***
	(0.0787)	(0.0767)	(0.0767)	(0.0768)
Experience: 19-25 years	0.2842***	0.2812***	0.2813***	0.3009***
	(0.0792)	(0.0774)	(0.0772)	(0.0779)
Experience: > 26 years	0.3814***	0.3641***	0.3724***	0.3748***
	(0.0770)	(0.0751)	(0.0752)	(0.0761)
German				Base Group
French				-0.0778*
				(0.0401)
Italian				-0.1124
				(0.0782)
Self-employed				-0.0193
				(0.0634)
Foreign				-0.1126**
				(0.0458)
Parttime				-0.0832
				(0.0574)
Constant	11.3726***	11.4734***	11.4200***	11.4525***
	(0.0681)	(0.0657)	(0.0707)	(0.0710)
Adjusted R-squared	0.0585	0.1069	0.1102	0.1226
R-squared	0.0713	0.1220	0.1283	0.1478
N	591	591	591	591
Prob>F	0.000	0.000	0.000	0.000

Source: Own calculations, based on CH-AES 2011; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A14 Variance decomposition for women

	Variance	Share of total Variance	Share of Explained Variance
Total Variance of ln(Earnings)	0.2277	100%	
Explained Variance of ln(Earnings)	0.0252	11,07%	100%
Components of Variance:			
Type of Education	0,0057	2,49%	22,46%
Subject Area	0,0057	2,50%	22,56%
Experience	0,0132	5,81%	52,48%
Linguistic Region	0,0033	1,47%	13,25%
Self-Employed	0,0003	0,14%	1,22%
Foreign	0,0010	0,44%	3,95%
Part-Time	0,0010	0,44%	3,95%
Components of Covariance			
Cov(Type. Subject Area)	-0,0035	-1,54%	-13,94%
Cov(Type. Linguistic Region)	-0,0004	-0,20%	-1,78%
Cov(Type. Self-Employed)	0,0000	0,00%	0,02%
Cov(Type. Foreign)	-0,0010	-0,42%	-3,83%
Cov(Type. Part-Time)	0,0000	0,02%	0,16%
Cov(Type. Experience)	0,0006	0,27%	2,43%
Cov(Subject Area. Linguistic Region)	0,0007	0,29%	2,60%
Cov(Subject Area. Self-Employed)	0,0000	-0,01%	-0,08%
Cov(Subject Area. Foreign)	0,0001	0,04%	0,40%
Cov(Subject Area. Part-Time)	0,0004	0,16%	1,43%
Cov(Subject Area. Experience)	0,0008	0,34%	3,03%
Cov(Linguistic Region. Self-Employed)	0,0000	0,01%	0,08%
Cov(Linguistic Region. Foreign)	-0,0001	-0,03%	-0,30%
Cov(Linguistic Region. Part-Time)	0,0001	0,05%	0,42%
Cov(Linguistic Region. Experience)	-0,0006	-0,25%	-2,22%
Cov(Self-Employed. Foreign)	-0,0001	-0,05%	-0,46%
Cov(Self-Employed. Part-Time)	0,0001	0,04%	0,37%
Cov(Self-Employed. Experience)	-0,0005	-0,20%	-1,80%
Cov(Foreign. Part-Time)	-0,0004	-0,17%	-1,51%
Cov(Foreign. Experience)	-0,0003	-0,15%	-1,33%
Cov(Part-Time. Experience)	-0,0009	-0,39%	-3,53%

Source: Own calculations, based on CH-AES 2011.

Table A15 Variance decomposition for men

	Variance	Share of total Variance	Share of Explained Variance
Total Variance of ln(Earnings)	0.2258	100%	
Explained Variance of ln(Earnings)	0.0334	14.78%	100%
Components of Variance:			
Type of Education	0.0033	1.45%	9.83%
Subject Area	0.0118	5.21%	35.22%
Experience	0.0168	7.44%	50.33%
Linguistic Region	0.0017	0.77%	5.24%
Self-Employed	0.0000	0.02%	0.10%
Foreign	0.0023	1.01%	6.81%
Part-Time	0.0007	0.33%	2.22%
Components of Covariance			
Cov(Type. Subject Area)	-0.0020	-0.88%	-5.98%
Cov(Type. Linguistic Region)	-0.0009	-0.39%	-2.62%
Cov(Type. Self-Employed)	-0.0001	-0.02%	-0.17%
Cov(Type. Foreign)	-0.0013	-0.57%	-3.85%
Cov(Type. Part-Time)	0.0000	-0.01%	-0.07%
Cov(Type. Experience)	-0.0004	-0.17%	-1.16%
Cov(Subject Area. Linguistic Region)	0.0008	0.34%	2.30%
Cov(Subject Area. Self-Employed)	0.0001	0.03%	0.20%
Cov(Subject Area. Foreign)	0.0007	0.30%	2.00%
Cov(Subject Area. Part-Time)	0.0007	0.33%	2.24%
Cov(Subject Area. Experience)	-0.0004	-0.18%	-1.20%
Cov(Linguistic Region. Self-Employed)	0.0000	0.01%	0.07%
Cov(Linguistic Region. Foreign)	0.0002	0.07%	0.46%
Cov(Linguistic Region. Part-Time)	0.0000	0.01%	0.05%
Cov(Linguistic Region. Experience)	-0.0011	-0.50%	-3.40%
Cov(Self-Employed. Foreign)	0.0000	0.00%	0.02%
Cov(Self-Employed. Part-Time)	0.0000	0.00%	-0.01%
Cov(Self-Employed. Experience)	-0.0002	-0.08%	-0.54%
Cov(Foreign. Part-Time)	-0.0001	-0.03%	-0.17%
Cov(Foreign. Experience)	0.0007	0.30%	2.03%
Cov(Part-Time. Experience)	0.0000	0.01%	0.05%

Source: Own calculations, based on CH-AES 2011.

Table A16 Mincer-type earnings regressions within each type of education

	Vocational		Academic		Mixed	
	ln(earnings)		ln(earnings)		ln(earnings)	
	Spec. 1	Spec. 2	Spec. 1	Spec. 2	Spec. 1	Spec. 2
Commercial	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Health	-0.2375***	-0.1138	0.0720	0.0922	-0.2119***	-0.1514*
	(0.0738)	(0.0731)	(0.0681)	(0.0686)	(0.0765)	(0.0770)
STEM	-0.0620	-0.1162*	-0.0053	-0.0214	-0.0181	-0.0267
	(0.0646)	(0.0621)	(0.0568)	(0.0553)	(0.0778)	(0.0815)
Social & Service	-0.4890***	-0.3800***	-0.2468***	-0.1973***	-0.3311***	-0.2940***
	(0.1188)	(0.1120)	(0.0748)	(0.0740)	(0.0996)	(0.0995)
Mixed Field	-0.2141***	-0.1630***	0.1099	0.1209	0.1624**	0.1464*
	(0.0527)	(0.0498)	(0.1416)	(0.1371)	(0.0810)	(0.0804)
Experience: 0-2 years	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Experience: 3-5 years	0.1006	0.0615	0.1126	0.1111	0.0384	0.0242
	(0.0804)	(0.0756)	(0.0892)	(0.0869)	(0.1034)	(0.1014)
Experience: 6-8 years	0.1467*	0.1270	0.3116***	0.3001***	0.1330	0.1514
	(0.0846)	(0.0791)	(0.0856)	(0.0834)	(0.0955)	(0.0945)
Experience: 9-13 years	0.2034***	0.2073***	0.3873***	0.3739***	0.1749*	0.1895*
	(0.0765)	(0.0727)	(0.0894)	(0.0877)	(0.1021)	(0.1026)
Experience: 14-18 years	0.1629*	0.1262	0.5123***	0.4788***	0.3068***	0.3129***
	(0.0835)	(0.0791)	(0.0883)	(0.0863)	(0.1078)	(0.1061)
Experience: 19-25 years	0.1608*	0.1673**	0.4804***	0.4607***	0.2894***	0.2698***
	(0.0877)	(0.0825)	(0.0876)	(0.0858)	(0.1014)	(0.1006)
Experience: > 26 years	0.2023**	0.1711**	0.4624***	0.4069***	0.4151***	0.4050***
	(0.0826)	(0.0797)	(0.0864)	(0.0858)	(0.1090)	(0.1072)
German		Base Group		Base Group		Base Group
French		-0.0651		-0.0662		0.0077
		(0.0489)		(0.0460)		(0.0553)
Italian		-0.0620		-0.1797**		-0.3035**
		(0.0933)		(0.0846)		(0.1253)
Gender (Men)		0.2794***		0.1389***		0.1675**
		(0.0486)		(0.0504)		(0.0664)
Self-employed		-0.3388***		0.1142		0.0278
		(0.0742)		(0.0719)		(0.0896)
Foreign		-0.0384		-0.0977**		-0.1030
		(0.0646)		(0.0481)		(0.0670)
Parttime		0.0206		-0.1623***		-0.0202
		(0.0510)		(0.0523)		(0.0690)
Constant	11.4393***	11.3317***	11.2261***	11.2805***	11.3736***	11.3282***
	(0.0642)	(0.0655)	(0.0769)	(0.0845)	(0.0830)	(0.0924)
Adjusted R-squared	0.0799	0.2042	0.1305	0.1897	0.1289	0.1727
R-squared	0.1036	0.2371	0.1478	0.2155	0.1614	0.2221
N	389	389	503	503	269	269
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000

Source: Own calculations, based on CH-AES 2011; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A17 Variance decomposition within each type of education

	Vocational			Academic			Mixed		
	Variance	Share of total	Share of explained	Variance	Share of total	Share of explained	Variance	Share of total	Share of explained
Total Variance of ln(Earnings)	0.1943	100%		0.2911	100%		0.2239	100%	
Explained Variance of ln(Earnings)	0.0461	23.71%	100%	0.0628	21.55%	100%	0.0497	22.21%	100%
Components of Variance:									
Subject Area	0.0079	4.08%	17.19%	0.0071	2.45%	11.36%	0.0155	6.94%	31.27%
Experience	0.0046	2.35%	0.10	0.0265	9.09%	42.16%	0.0172	7.69%	34.61%
Gender (Male)	0.0196	10.06%	0.42	0.0048	1.65%	7.66%	0.0070	3.11%	14.00%
Linguistic Region	0.0008	0.44%	0.02	0.0026	0.90%	4.17%	0.0047	2.10%	9.43%
Self-Employed	0.0087	4.47%	0.19	0.0013	0.45%	2.09%	0.0001	0.03%	0.14%
Foreign	0.0001	0.08%	0.00	0.0021	0.73%	3.37%	0.0020	0.88%	3.97%
Part-Time	0.0001	0.05%	0.00	0.0058	2.00%	9.27%	0.0001	0.04%	0.18%
Components of Covariance									
Cov(Subject Area. Gender)	0.0019	1.00%	0.04	-0.0008	-0.27%	-1.26%	0.0044	1.95%	8.76%
Cov(Subject Area. Linguistic Region)	0.0005	0.26%	0.01	0.0007	0.23%	1.06%	0.0019	0.83%	3.74%
Cov(Subject Area. Self-Employed)	0.0021	1.09%	0.05	0.0007	0.25%	1.18%	-0.0002	-0.10%	-0.46%
Cov(Subject Area. Foreign)	0.0002	0.08%	0.00	0.0000	0.00%	0.00%	-0.0009	-0.40%	-1.78%
Cov(Subject Area. Part-Time)	-0.0002	-0.11%	0.00	0.0011	0.39%	1.79%	0.0005	0.21%	0.96%
Cov(Subject Area. Experience)	-0.0005	-0.26%	-0.01	0.0024	0.81%	3.75%	-0.0032	-1.41%	-6.35%
Cov(Gender. Linguistic Region)	-0.0002	-0.12%	-0.01	0.0000	0.00%	-0.01%	0.0005	0.23%	1.03%
Cov(Gender. Self-Employed)	0.0012	0.62%	0.03	0.0003	0.11%	0.53%	-0.0001	-0.03%	-0.14%
Cov(Gender. Foreign)	0.0001	0.07%	0.00	0.0000	0.01%	0.04%	0.0001	0.03%	0.11%
Cov(Gender. Part-Time)	-0.0012	-0.64%	-0.03	0.0045	1.54%	7.14%	0.0008	0.37%	1.67%
Cov(Gender. Experience)	0.0019	1.00%	0.04	0.0028	0.98%	4.53%	0.0007	0.33%	1.49%
Cov(Linguistic Region. Self-Employed)	0.0001	0.05%	0.00	0.0000	-0.01%	-0.07%	-0.0001	-0.05%	-0.21%
Cov(Linguistic Region. Foreign)	0.0001	0.06%	0.00	-0.0003	-0.09%	-0.40%	-0.0003	-0.15%	-0.69%
Cov(Linguistic Region. Part-Time)	0.0000	-0.02%	0.00	-0.0003	-0.10%	-0.46%	0.0001	0.03%	0.12%
Cov(Linguistic Region. Experience)	-0.0001	-0.08%	0.00	-0.0011	-0.39%	-1.80%	-0.0002	-0.09%	-0.39%
Cov(Self-Employed. Foreign)	0.0000	0.01%	0.00	0.0004	0.15%	0.69%	0.0000	-0.01%	-0.06%
Cov(Self-Employed. Part-Time)	-0.0001	-0.06%	0.00	-0.0002	-0.06%	-0.27%	0.0000	0.00%	-0.01%
Cov(Self-Employed. Experience)	-0.0017	-0.88%	-0.04	0.0017	0.59%	2.75%	0.0000	0.00%	0.00%
Cov(Foreign. Part-Time)	0.0000	0.01%	0.00	-0.0006	-0.21%	-0.95%	-0.0002	-0.07%	-0.33%
Cov(Foreign. Experience)	0.0000	0.01%	0.00	0.0004	0.12%	0.56%	-0.0004	-0.20%	-0.88%
Cov(Part-Time. Experience)	0.0002	0.08%	0.00	0.0007	0.24%	1.09%	-0.0001	-0.05%	-0.21%

Source: Own calculations, based on CH-AES 2011.

Table A18 Mincer-type earnings regressions within each subject area

	Commercial		Health		STEM		Social & Service		Combined Subject Areas	
	ln(earnings)		ln(earnings)		ln(earnings)		ln(earnings)		ln(earnings)	
	Spec. 1	Spec. 2	Spec. 1	Spec. 2	Spec. 1	Spec. 2	Spec. 1	Spec. 2	Spec. 1	Spec. 2
Vocational	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Academic	-0.0193	0.0124	0.2575***	0.2098**	0.0860	0.1638**	0.2175	0.1726	0.2924**	0.2842**
	(0.0526)	(0.0541)	(0.0951)	(0.0959)	(0.0670)	(0.0675)	(0.1620)	(0.1629)	(0.1243)	(0.1194)
Mixed	-0.0247	0.0041	-0.0054	-0.0068	0.1106	0.1657*	0.0953	0.1019	0.3288***	0.3279***
	(0.0606)	(0.0593)	(0.1037)	(0.1038)	(0.0866)	(0.0862)	(0.1818)	(0.1817)	(0.0739)	(0.0720)
Exp: 0-2 years	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group	Base Group
Exp: 3-5	0.0548	0.0241	0.0896	0.0230	0.1780*	0.1747*	-0.3916*	-0.4080*	0.2455**	0.2508**
	(0.0933)	(0.0891)	(0.1367)	(0.1341)	(0.1037)	(0.1014)	(0.2075)	(0.2139)	(0.1098)	(0.1068)
Exp: 6-8	0.1667*	0.1544*	0.3050**	0.2318*	0.1955*	0.2440**	0.0568	0.0821	0.2728**	0.2707**
	(0.0852)	(0.0816)	(0.1339)	(0.1302)	(0.1099)	(0.1069)	(0.1733)	(0.1735)	(0.1175)	(0.1133)
Exp: 9-13	0.1717**	0.1846**	0.3019**	0.2085	0.4358***	0.4183***	0.3816**	0.4567**	0.2410**	0.2280**
	(0.0849)	(0.0826)	(0.1439)	(0.1412)	(0.1118)	(0.1086)	(0.1840)	(0.1877)	(0.1071)	(0.1027)
Exp: 14-18	0.3226***	0.3072***	0.1794	0.0322	0.5673***	0.5434***	0.1392	0.1405	0.3271**	0.3462***
	(0.0904)	(0.0872)	(0.1492)	(0.1525)	(0.1038)	(0.1016)	(0.1726)	(0.1771)	(0.1340)	(0.1280)
Exp: 19-25	0.2240**	0.2320**	0.3652***	0.2618*	0.5594***	0.5191***	0.2713	0.3609*	0,1508	0.1794
	(0.0946)	(0.0912)	(0.1371)	(0.1357)	(0.1022)	(0.1016)	(0.1859)	(0.1866)	(0,1260)	(0.1218)
Exp: > 26	0.2368**	0.2210**	0.3791***	0.2844**	0.5280***	0.5052***	0,1698	0.2235	0.4617***	0.3978***
	(0.0922)	(0.0900)	(0.1348)	(0.1320)	(0.0993)	(0.0995)	(0.2034)	(0.2151)	(0.1341)	(0.1289)
German		Base Group		Base Group		Base Group		Base Group		Base Group
French		-0.0251		-0.0322		-0.0038		-0.0706		-0.1625**
		(0.0483)		(0.0770)		(0.0541)		(0.1130)		(0.0672)
Italian		-0.0842		-0.4496***		-0.1830*		-0.0542		-0.0741
		(0.1002)		(0.1580)		(0.1099)		(0.1726)		(0.1329)
Men		0.1584***		0.2208**		0.2292***		0.1090		0.2512***
		(0.0499)		(0.0991)		(0.0623)		(0.1247)		(0.0699)
Self-emp.		0.1924**		0.2084**		-0.1563*		-0.4506***		-0.2559**
		(0.0924)		(0.0997)		(0.0903)		(0.1683)		(0.0997)
Foreign		-0.1093*		-0.0137		-0.0805		-0.0902		-0.0372

		(0.0578)		(0.0961)		(0.0561)		(0.1417)		(0.0861)
Parttime		-0.1826***		-0.0077		-0.0842		-0.0745		0.0510
		(0.0570)		(0.0859)		(0.0653)		(0.1216)		(0.0724)
Constant	11.4176***	11.3946***	11.1229***	11.1822***	11.0962***	10.9596***	10.9787***	11.0763***	11.1358***	11.0868***
	(0.0709)	(0.0737)	(0.1104)	(0.1224)	(0.0983)	(0.1064)	(0.1908)	(0.2082)	(0.0871)	(0.0986)
Adj R	0.0249	0.1219	0.1035	0.1849	0.1436	0.2053	0.0658	0.0986	0.1427	0.2486
R	0.0454	0.1543	0.1416	0.2456	0.1662	0.2420	0.1357	0.2166	0.1813	0.3077
N	381	381	189	189	304	304	108	108	179	179
Prob>F	0.026	0.000	0.000	0.000	0.000	0.000	0.062	0.044	0.000	0.000

Source: Own calculations, based on CH-AES 2011; standard errors are reported in parentheses; * statistically significant at the 0.1 level; ** at the 0.05 level; *** at the 0.01 level.

Table A19 Variance decomposition within each subject area

	Commercial			Health			STEM		
	Variance	Share of total	Share of explained	Variance	Share of total	Share of explained	Variance	Share of total	Share of explained
Total Variance of ln(Earnings)	0.2000	100%		0.2826	100%		0.2432	100%	
Explained Variance of ln(Earnings)	0.0308	15.43%	100%	0.0694	24.56%	100%	0.0589	24.20%	100%
Components of Variance:									
Type of Education	0.0000	0.02%	0.10%	0.0114	4.05%	16.49%	0.0045	1.87%	7.73%
Experience	0.0094	4.70%	30.48%	0.0135	4.79%	19.49%	0.0350	14.40%	59.51%
Gender (Male)	0.0063	3.14%	20.33%	0.0086	3.05%	12.41%	0.0106	4.36%	18.03%
Linguistic Region	0.0004	0.21%	1.36%	0.0108	3.81%	15.52%	0.0018	0.76%	3.13%
Self-Employed	0.0021	1.05%	6.83%	0.0064	2.28%	9.28%	0.0020	0.84%	3.48%
Foreign	0.0020	1.00%	6.49%	0.0000	0.01%	0.04%	0.0015	0.62%	2.55%
Part-Time	0.0064	3.19%	20.70%	0.0000	0.01%	0.02%	0.0012	0.51%	2.10%
Components of Covariance									
Cov(Type of Education. Gender)	0.0000	0.01%	0.05%	0.0033	1.18%	4.82%	-0.0025	-1.04%	-4.29%
Cov(Type of Education. Linguistic Region)	0.0000	-0.02%	-0.13%	-0.0009	-0.30%	-1.23%	0.0000	0.00%	0.01%
Cov(Type of Education. Self-Employed)	0.0000	0.01%	0.09%	0.0028	0.99%	4.04%	0.0002	0.07%	0.30%
Cov(Type of Education. Foreign)	-0.0002	-0.08%	-0.52%	0.0000	0.01%	0.02%	-0.0013	-0.52%	-2.16%
Cov(Type of Education. Part-Time)	0.0000	0.01%	0.04%	0.0001	0.05%	0.19%	-0.0007	-0.28%	-1.16%
Cov(Type of Education. Experience)	0.0001	0.06%	0.39%	0.0030	1.06%	4.31%	-0.0045	-1.83%	-7.57%
Cov(Gender. Linguistic Region)	-0.0001	-0.06%	-0.42%	0.0004	0.15%	0.60%	-0.0003	-0.11%	-0.44%
Cov(Gender. Self-Employed)	-0.0002	-0.09%	-0.56%	0.0031	1.09%	4.42%	0.0000	0.02%	0.07%
Cov(Gender. Foreign)	0.0008	0.39%	2.52%	-0.0001	-0.02%	-0.09%	0.0005	0.21%	0.88%
Cov(Gender. Part-Time)	0.0055	2.77%	17.98%	0.0003	0.12%	0.50%	0.0024	0.99%	4.11%
Cov(Gender. Experience)	0.0010	0.48%	3.08%	0.0029	1.01%	4.11%	0.0084	3.46%	14.27%
Cov(Linguistic Region. Self-Employed)	-0.0002	-0.10%	-0.65%	0.0019	0.68%	2.76%	0.0001	0.03%	0.11%
Cov(Linguistic Region. Foreign)	-0.0001	-0.03%	-0.17%	-0.0001	-0.03%	-0.10%	0.0001	0.02%	0.10%
Cov(Linguistic Region. Part-Time)	0.0001	0.06%	0.38%	0.0000	-0.01%	-0.04%	0.0000	0.00%	0.01%
Cov(Linguistic Region. Experience)	-0.0004	-0.20%	-1.28%	-0.0003	-0.12%	-0.49%	-0.0008	-0.35%	-1.43%
Cov(Self-Employed. Foreign)	0.0002	0.10%	0.68%	0.0001	0.04%	0.14%	-0.0002	-0.07%	-0.30%
Cov(Self-Employed. Part-Time)	-0.0006	-0.29%	-1.85%	0.0001	0.02%	0.09%	0.0003	0.13%	0.55%
Cov(Self-Employed. Experience)	0.0006	0.32%	2.10%	0.0019	0.68%	2.78%	-0.0021	-0.88%	-3.64%
Cov(Foreign. Part-Time)	-0.0005	-0.25%	-1.65%	0.0000	0.00%	-0.01%	-0.0001	-0.05%	-0.20%
Cov(Foreign. Experience)	-0.0001	-0.06%	-0.38%	-0.0001	-0.02%	-0.09%	0.0020	0.80%	3.31%
Cov(Part-Time. Experience)	-0.0019	-0.93%	-6.00%	0.0000	0.01%	0.03%	0.0006	0.23%	0.95%

Source: Own calculations, based on CH-AES 2011.

	Social & Service			Combined Subject Areas		
	Variance	Share of total	Share of explained	Variance	Share of total	Share of explained
Total Variance of ln(Earnings)	0.3101	100%		0.2055	100%	
Explained Variance of ln(Earnings)	0.0671	21.66%	100%	0.0632	30.77%	100%
Components of Variance:						
Type of Education	0.0035	1.14%	5.28%	0.0229	11.17%	36.30%
Experience	0.0536	17.29%	79.82%	0.0122	5.92%	19.23%
Gender (Male)	0.0029	0.94%	4.34%	0.0158	7.69%	24.99%
Linguistic Region	0.0011	0.37%	1.70%	0.0054	2.64%	8.58%
Self-Employed	0.0217	7.00%	32.32%	0.0060	2.90%	9.42%
Foreign	0.0012	0.40%	1.85%	0.0002	0.09%	0.31%
Part-Time	0.0014	0.45%	2.08%	0.0006	0.30%	0.97%
Components of Covariance						
Cov(Type of Education. Gender)	0.0004	0.11%	0.52%	0.0040	1.94%	6.32%
Cov(Type of Education. Linguistic Region)	-0.0003	-0.10%	-0.45%	-0.0028	-1.37%	-4.45%
Cov(Type of Education. Self-Employed)	0.0030	0.98%	4.51%	0.0001	0.04%	0.12%
Cov(Type of Education. Foreign)	-0.0002	-0.07%	-0.32%	-0.0009	-0.43%	-1.39%
Cov(Type of Education. Part-Time)	-0.0002	-0.07%	-0.31%	-0.0007	-0.34%	-1.09%
Cov(Type of Education. Experience)	-0.0035	-1.13%	-5.23%	0.0000	0.02%	0.07%
Cov(Gender. Linguistic Region)	-0.0001	-0.02%	-0.08%	-0.0011	-0.53%	-1.71%
Cov(Gender. Self-Employed)	-0.0024	-0.77%	-3.53%	0.0010	0.51%	1.65%
Cov(Gender. Foreign)	-0.0005	-0.16%	-0.73%	0.0006	0.31%	1.01%
Cov(Gender. Part-Time)	0.0019	0.62%	2.88%	-0.0027	-1.29%	-4.20%
Cov(Gender. Experience)	-0.0023	-0.75%	-3.45%	0.0026	1.27%	4.13%
Cov(Linguistic Region. Self-Employed)	-0.0002	-0.08%	-0.36%	0.0003	0.15%	0.49%
Cov(Linguistic Region. Foreign)	0.0000	-0.01%	-0.04%	0.0003	0.14%	0.46%
Cov(Linguistic Region. Part-Time)	-0.0001	-0.02%	-0.09%	0.0000	-0.01%	-0.04%
Cov(Linguistic Region. Experience)	-0.0009	-0.30%	-1.36%	-0.0019	-0.94%	-3.06%
Cov(Self-Employed. Foreign)	0.0012	0.39%	1.80%	0.0000	0.00%	0.00%
Cov(Self-Employed. Part-Time)	-0.0012	-0.38%	-1.74%	0.0000	-0.02%	-0.06%
Cov(Self-Employed. Experience)	-0.0101	-3.26%	-15.05%	0.0017	0.84%	2.74%
Cov(Foreign. Part-Time)	0.0001	0.02%	0.08%	0.0000	0.01%	0.04%
Cov(Foreign. Experience)	0.0000	0.00%	0.02%	-0.0002	-0.10%	-0.34%
Cov(Part-Time. Experience)	-0.0030	-0.96%	-4.45%	-0.0003	-0.15%	-0.49%

Source: Own calculations, based on CH-AES 2011.

Chapter 6

Summary and Conclusions

Many researchers have investigated the importance of education on societal, economic, and innovative activities. However, empirical studies analyzing the effect of differences in educational structures, i.e., studies differentiating among dimensions other than the acquired number of years of schooling, on these outcomes are scarce. Differences in educational structures are manifold and involve the factors level (the acquired numbers of years of schooling), type (academic or vocational education), and field of education (the subject areas, e.g., health, engineering, or business). The aim of this dissertation was to provide a detailed analysis of the effect of different dimensions of educational structures on economic outcomes at the individual level and at the level of the entire economy. Throughout the chapters, yielding important insights how and why education affects innovation and earnings and thereby contributing to the literature on innovation and education economics, I focus on dimensions of educational structures that have thus far been neglected in the literature.

The effect of tertiary vocational education on regional innovation

In the analysis at the level of the economy, I investigate the effect of a particular type of education that has thus far not been analyzed on innovation: tertiary vocational education. The literature studying the impact of education on innovation has concentrated on the effect of academic universities. As the research has mainly focused on tertiary academic education and thus far neglected the second type, tertiary vocational education, the resulting picture of the effect of education on innovation was fragmented. Not taking into account this missing part might lead to misleading conclusions. In the second chapter of this dissertation, I complete this missing part by analyzing the effect of tertiary vocational education institutions on innovation.

To analyze the effect of tertiary vocational education on innovation, I exploit the establishment of UAS, educational institutions that are equivalent to academic universities in terms of level (they are both located at the tertiary level) but that differ in terms of type: Their teaching and research include vocational education and applied research. I argue that these underlying characteristics of tertiary vocational education, namely, the combination of sound vocational knowledge and applied research skills, lead to an increase in regional innovation activities through spillovers of UAS. I hypothesize that these spillovers appear due to the production of graduates with a new type of human capital (who enter the labor market and increase its quality) and due to collaboration between firms and UAS. The results of my empirical analyses confirm my hypotheses and show a substantial impact on regional innovation activities; a substantial portion of the innovation effect is related to graduates entering the labor market. Moreover, the use of the difference-in-differences method and a large number of robustness checks allow the causal interpretation of these empirical findings.

This chapter thus contributes to the literature on innovation and education economics by demonstrating the effect of tertiary vocational education on regional innovation. My analyses thus show that obtaining an academic education, offered by institutions that conduct predominantly basic research, is not the only way to foster innovation. Moreover, my analyses emphasize the importance of investigating the underlying characteristics of educational institutions and, consequently, the different dimensions of educational structures. These different dimensions—in my analyses, the focus of the UAS on vocational education and applied research—allow answering the question of why a particular educational structure has an impact on the economy.

Tertiary vocational education and innovation – A trade-off between innovation quantity and quality?

While UAS have a substantial impact on innovation quantity, their effect on innovation quality remains unclear. To analyze whether the establishment of UAS has led to a trade-off between patent quantity and patent quality, or whether UAS increased the quantity and quality of innovation at the same time, I investigate the impact of UAS on a number of qualitative patent indicators well established in the literature. The results of the difference-in-differences estimations show a statistically significant increase in all quality measures. Thus the establishment of UAS led not only to a substantial increase in the patents' economic value for the patent holder but also to an increase in the technological value of the innovation and to an increase in the patents' social value, i.e., the positive externalities for those not possessing the patent. A trade-off between patent quantity and quality is therefore unlikely. In contrast, the effect of UAS on regional innovation activities might be even higher, as they are likely to cause technological spillovers.

Tertiary vocational education and innovation – Who profits from Universities of Applied Sciences?

Firms profit from these technological spillovers and from spillovers generated by UAS, such as UAS graduates entering the labor market or collaboration of firms with UAS. To analyze whether different types of firms benefit similarly from such spillovers, I estimate the effect of UAS on different types of patent applicants, i.e., proxies for large firms, small and medium-sized firms, and new firms. My empirical results show that all types of applicants profit from the establishment of UAS. The effect on heavy applicants—a proxy for large firms—is, however, largest. UAS thus increased innovation activities of applicants that had already heavily patented before the UAS reform, i.e., at the intensive margin. In addition, UAS increased the number of applicants that did not patent before the reform, showing the effect of tertiary vocational education at the extensive margin. As these first-time applicants are a proxy for firms that did not patent before the reform and for new firms such as start-ups, the establishment of UAS not only increased regional patenting activities but also most likely affected regional entrepreneurial activities.

Whether the location of applicants determines the size of the innovation effect is a question I tackle in the second part of this chapter. Rural areas generally exhibit poorer economic conditions than metropolitan areas exhibit. To analyze whether the establishment of UAS improves these economic conditions, I estimate the effect of UAS on rural areas in the treatment group, relative to rural areas in the control group. My results show that rural areas profit from spillovers of UAS.

The effect of the type and the field of education on determining risk

The analysis of the factor type of education and its effect on innovation demonstrates the importance of analyzing different educational structures in an economy. Whether educational structures matter as much at the individual level remains unclear.

In the analysis at the individual level, I focus on the factors type and field of education, keeping the level constant at the tertiary level, and study their importance for the educational decision-making of individuals. For type of education (i.e., vocational vs. academic), the literature shows mixed empirical evidence for returns to academic and vocational education; for the field, the results are consistent and show the highest returns for business, health, and engineering, and the lowest returns for the social sciences, the humanities and for education. While both educational factors appear in the literature, most studies focus either on the type or on the field of education. Moreover, most research focuses on average returns to of the human capital investments, neglecting a second fundamental aspect of educational decisions: the risk.

To analyze the effect of the different dimensions of educational structures at the individual level, I focus on the relative importance of the educational factors, namely, the type and the field of education, in determining the variance in earnings. I thereby consider an essential aspect of the individual decision-making for investments in human capital: the risk associated with these decisions. For the factor type of education, I differentiate among vocational, academic and mixed educational careers; for the field, I distinguish among the subject areas commercial, STEM, health, social & service, and combined subject areas. My empirical results show that the variance attributable to the field of education is nearly twice as large as the variance attributable to the type of education. Educational decisions made among fields of education (e.g., business vs. health) are thus riskier than decisions made among types of education (vocational vs. academic).

This empirical evidence sheds a new light on the discussion regarding educational tracking. The literature thus far primarily addressed the decision between vocational and academic education, mainly attributing vocational education as appropriate for low-income prospects. However, tertiary-level earnings between these two tracks vary much less than do earnings among different fields of education, i.e., the choice for particular subject areas or occupations. The discussion on educational decisions should thus devote as much attention to the choice of fields as to the types of education. A second important finding of this chapter relates to combinations of different types of education. The results show that combining vocational and academic education yields high returns and low variances. These mixed educational careers are thus profitable but not riskier. Allowing such combinations between academic and vocational education is thus a critical component of the structure of an educational system. Such educational careers are only possible in an education system that allows permeability because otherwise the transition across fields, types, and levels becomes too difficult and too unrealistic.

Implications

The research findings of the four chapters reveal important insights for researchers and policy makers. As Drucker and Goldstein (2007) argue, focusing on the diversity of higher education systems reveals why education has an impact on economic outcomes. Throughout the four chapters, I focus on this diversity of higher education, analyzing distinct dimensions and functions of educational structures—i.e., the factors type and the field of education—and demonstrate their impact on outcomes at the level of the economy and at that of individuals. In this dissertation, I thus clearly demonstrate that education is not a homogenous good. Focusing on heterogeneity in education, i.e., different dimensions of educational structures, is therefore essential when analyzing, evaluating or designing (national) educational systems.

My analyses show that this heterogeneity in education, in particular, the combination of different dimensions of educational structures, is essential for outcomes of the economy and of individuals. In their teaching and research, UAS combine sound vocational knowledge with applied research skills. This combination results in a substantial increase in the economy's innovative performance. Similarly, individuals who combine academic and vocational education show large returns to education. Thus the combination of different types of education generates a positive impact on both the economy and the individuals. In addition, these results highlight the importance of permeability in the national education system.

Combining different dimensions of educational structures, such as types of education, does not necessarily lead to a trade-off of economic outcomes. The combination of vocational knowledge with applied research skills leads to an increase in both innovation quantity and innovation quality. At the level of the economy, such a combination does thus not lead to conflictive interests, such as quantity vs. quality. At the individual level, my empirical results show that educational careers including vocational and academic education exhibit not only large returns but also low variances, i.e., low risk. Combining different dimensions of educational structures, therefore, does not result in a trade-off of economic outcomes, i.e., profit vs. risk, at the individual level.

Finally, combining my research findings at the level of the economy and at the level of the individuals shows that different dimensions of educational structures—particularly the combinations of different types of education—allow the alignment of the economy's and the individuals' interests. Regarding the interests of the economy, UAS have a close relationship with firms: Teaching and research of UAS focus on applied research and are thus targeted towards the economy's needs. Similarly, UAS graduates acquire human capital that includes both practical and scientific knowledge. These graduates have thus skills that are attractive to firms because these skills foster the transfer of technology and knowledge and lead to innovation. Regarding the interests of individuals, all types of education—vocational, academic, and mixed—yield high returns to education and are thus a profitable investment for individuals. Moreover, the risk attributable to the factor type of education is much lower than the risk attributable to the field of education. Studying at a UAS is thus attractive to individuals. The interests of these individuals and the interests of the economy, therefore, do not collide. Consequently, an education system whose structures include the different factors, type and field—and even different combinations of these factors—allows the alignment of interests of the economy and of the individuals.

Future research

In the next step, it would be fruitful to investigate in more detail the different channels leading to the increase in regional innovation activities. Whether the effect depends on UAS professors producing patents, on cooperation between UAS and firms, or on collaborations between UAS and other research institutes remains unclear. With the use of further data sources, it might be possible to answer these questions.

Second, my analyses show that the establishment of UAS have a heterogeneous effect on different types of applicants. The results show that the main drivers of the effect are heavy applicants, a proxy for large firms. These heavy applicants, who already patented before the reform, produce even more patents after the establishment of UAS. The results further show an increase in first-time applicants, who are a proxy for newly founded firms that start patenting or firms that did not patent before the reform, i.e., most likely small and medium-sized firms. On the one hand, future research might use employer data to investigate factors causing these differences. Why do different types of firms profit differently from UAS? Which role do available resources, economies of scale and scope, as well as the size and the composition of R&D team play in determining these differences? On the other hand, as the variables "applicant size" and "first-time applicants" are not perfect proxies for the size of the firm and for entrepreneurs, future research might match patent data with employer data to investigate more elaborately the effect of UAS on different types of firms and on regional entrepreneurial activities.

Third, my analyses show that UAS increase regional patenting activities in rural areas. Future research might investigate whether UAS constitute a means to overcome economic disparities between rural and metropolitan areas.

Fourth, all three chapters on the establishment of UAS show indications for different forms of externalities of the establishment. For example, the indicator forward citations mirrors not only the economic value of a patent for the patent holder but also the patent's social value, i.e., the value of the invention for those not holding the patents. The establishment of UAS thus increased technological spillovers. A second form of externalities entails the effect of UAS on the number of first-time applicants. As first-time applicants include newly founded firms, such as start-ups, these first-time applicants are also a proxy for regional entrepreneurial activities. A positive impact of UAS on regional entrepreneurial activities using employer data is therefore likely. A third form of externalities are UAS graduates entering the labor market. The establishment of UAS has led to a change of highly skilled labor. Whether this change of labor had a positive or a negative effect on the graduates of other educational types, fields or levels is thus far unclear. These three forms of externalities might constitute important research projects.

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